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Systemic Risk Monitoring ("SysMo") Toolkit—A User Guide

Nicolas Blancher, Srobona Mitra, Hanan Morsy, Akira Otani, Tiago Severo, and Laura Valderrama

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Abstract

There has recently been a proliferation of new quantitative tools as part of various initiatives to improve the monitoring of systemic risk. The "SysMo" project takes stock of the current toolkit used at the IMF for this purpose. It offers detailed and practical guidance on the use of current systemic risk monitoring tools on the basis of six key questions policymakers are likely to ask. It provides "how-to" guidance to select and interpret monitoring tools; a continuously updated inventory of key categories of tools ("Tools Binder"); and suggestions on how to operationalize systemic risk monitoring, including through a systemic risk "Dashboard." In doing so, the project cuts across various country-specific circumstances and makes a preliminary assessment of the adequacy and limitations of the current toolkit.

JEL Classification Numbers: G12, G29, C51

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Glossary

BSA	Balance Sheet Approach
CAMELS	Capital adequacy, Asset quality, Management, Earnings, Liquidity, and Sensitivity to market risk
CAR	Capital Adequacy Ratio
CCA	Contingent Claims Analysis
CCB	Committee on Capacity Building
CIMDO	Consistent Information Multivariate Density Optimizing
DiDe	Distress Dependence
DNL-SRMS	De Nicolo and Lucchetta Systemic Risk Monitoring System
CoVaR	Conditional Value at Risk
DSA	Debt Sustainability Analysis
DSGE	Dynamic Stochastic General Equilibrium
DtD	Distance-to-Default
EDF	Expected Default Frequency
FSaR	Financial System-at-Risk
FSI	Financial Soundness Indicator
GDP	Gross Domestic Product
GDPaR	GDP-at-Risk
JDI	Joint Distress Indicator
JPoD	Joint Probability of Default
KMV	Kealhofer, McQuown and Vasicek
LGD	Loss Given Default
MSCI	Morgan Stanley Capital International
OOS	On-the-run Off-the-run Spread
PCA	Principal Components Analysis
PCE	Probability of Cascade Effects
SCCA	Systemic Contingent Claims Analysis
SLRI	Systemic Liquidity Risk Indicator
VaR	Value at Risk
VAR	Vector Autoregression
VD	Variance Decomposition
VIX	Volatility Index

I. INTRODUCTION[1]

1. **Macroprudential policymakers need to know when to act.** Policies to mitigate system-wide risks should be based on detailed information on where and when such risks are building up and which channels may amplify their impact on the broader economy.

2. **This paper aims to clarify the nature and use of the systemic risk monitoring tools that are currently available.** Building on earlier surveys,[2] it looks at all dimensions of systemic risk and assesses the tools' ability to capture these dimensions. The paper offers suggestions on how to use the tools, taking into account their nature, focus, and relative merits and limitations. It also focuses on the systemic risk signals, including their timeliness, the types of risks they cover, and ways of interpreting them. However, this paper does not analyze the direct relevance of specific systemic risk measures for the selection of appropriate macro-prudential policy tools (and their calibration).

3. **This paper offers guidance on how to select the best set of available tools under various circumstances**. Effective risk monitoring should be based on a clear understanding that: (i) policymakers should not expect to find "all-in-one" tools, because the reliability of systemic risk monitoring tools depends on the circumstances in which they are used; and (ii) policymakers should take into account several potential sources of risk by using a range of tools at any point in time. Against this background, the objective of this paper is to identify those tools (or combinations of tools) that are most effective in measuring a specific dimension of systemic risk. It provides policymakers with some general principles based on cross-country analyses, but it also encourages practitioners to calibrate the toolbox in view of country-specific circumstances.

4. **The structure of this guide follows a practical approach.** After a brief introduction to systemic risk and the key features of the existing toolkit, the guide discusses a range of systemic risk monitoring tools. They include, for example, tools focusing on a narrow (but potentially systemically relevant) sectoral perspective, as well as tools to measure the risk of a systemic crisis. There are four complementary ways to access and use this guide (Figure 1):

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[1] The authors would like to thank, without implicating, Jan Brockmeijer, Stijn Claessens, Gianni de Nicolo, Dimitri Demekas, Laura Kodres, Jacek Osinski, Ratna Sahay, Amadou Sy, and José Viñals for very helpful discussions and suggestions; Serkan Arslanalp, Ivailo Arsov, Marcos Chamone, Marco Espinosa-Vega, Dale Gray, Deniz Igan, Andy Jobst, Sonia Muñoz, Li Lian Ong, Miguel Segoviano, Juan Sole, and Takahiro Tsuda for constructive comments pertaining to the tools they developed; and other reviewers at the IMF. The authors plan to regularly update and expand the guidance note as new tools are developed.

[2] See in particular IMF-Financial Stability Board (2010), IMF (2009a), Basel Committee of Banking Supervision (2012), and Bisias et al (2012).

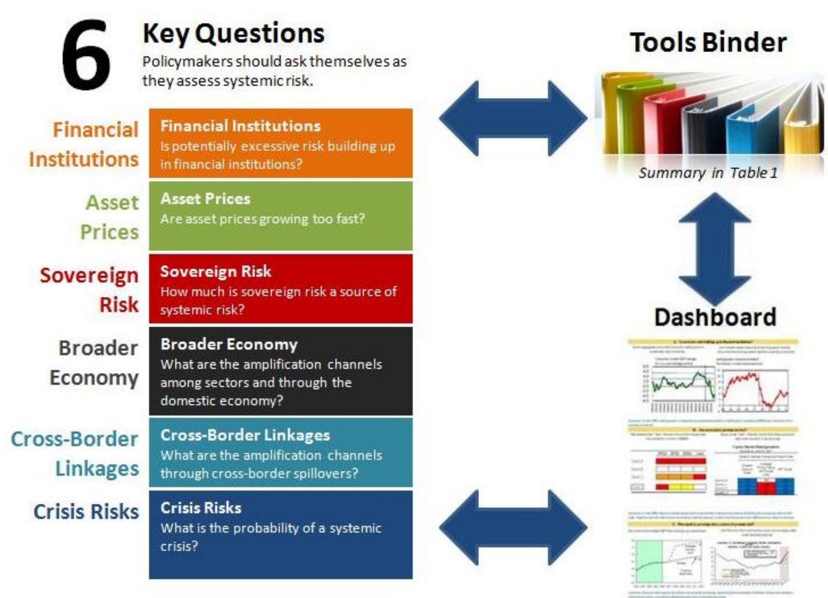
- An *in-depth discussion of six key questions* on systemic risk that policymakers are likely to ask (Figure 1): Is potentially excessive risk building up in financial institutions? Are asset prices growing too fast? How much is the sovereign risk a source of systemic risk? What are the amplification channels among sectors and through the broader domestic economy? What are the amplification channels through cross-border spillovers? What is the probability of a systemic crisis? In addressing each question, the emphasis is put on *combinations* of relevant tools in light of their relative merits and complementarities.

- A *living inventory ("Tools Binder")* that offers a two-page snapshot of each tool, summarizing its key properties (methodology, coverage, interpretation, data requirements, etc) and providing a concrete example of its use.

- A sample systemic risk *Dashboard* for a fictitious advanced country that illustrates how, in a specific country context, various complementary tools can be combined to monitor key sources of systemic risk.

- *Tool selection tables* that summarize which tools are available for which purpose and country category, thereby helping users to readily identify the most relevant tools.

Figure 1. Structure of the Guide



5. **Finally, the paper concludes by highlighting how well the various dimensions of systemic risk are covered** by the current toolkit, and by identifying some key analytical gaps that could benefit from future research.

II. APPROACHING SYSTEMIC RISK

A. What is Systemic Risk?

6. **Lessons from past and current crises highlight key sources of systemic risk, the evolution of these risks over time, and the underlying macro-financial linkages:**

Definition. There is an evolving literature on systemic risk measurement covering a wide range of approaches. In the context of this paper, systemic risk is defined as risk that originates within, or spreads through, the financial sector (e.g., due to insufficient solvency or liquidity buffers in financial institutions), with the potential for severe adverse effects on financial intermediation and real output. The objective of macroprudential policy is, therefore, to limit *system-wide financial risk* (IMF, 2011a) by enabling policymakers to know better when to "sound the alarm" and implement policy responses.

Phases. Past crisis episodes show that different sources of risk and shock transmission channels can emerge at the same time or in complex sequences, including through multiple feedback effects. However, from an analytical perspective, it may be useful to distinguish between key phases in which crisis-related events unfold. At the same time, policymakers should be cognizant of macro-financial linkages during each phase. Ultimately, most systemic crises involve feedback effects between the real economy and the financial sector, including across countries.

Theoretical and empirical models dealing with interactions between the financial sector and the real economy, as well as between cross-border transmission channels, are useful for monitoring purposes in general.

- *Buildup phase.* Systemic risk builds up over time, and this could reflect several underlying reasons. The financial system may have high exposure to an overheating sector, or be subject to increased risk-taking (e.g., due to competition for market-share or lax supervision), including through financial innovation. The risk buildup could also be related to growing cross-border exposures and funding sources. During this phase, systemic risk measures could focus on assessing the likelihood of a systemic crisis (Figure 2), taking into account the evolving balance between potential financial losses and existing buffers designed to absorb these losses.

- *Shock materialization*. At that point, the crisis is about to start. Mounting imbalances or excessive risk-taking make the financial system fragile and susceptible to exogenous shocks (e.g., GDP or fiscal shocks, exchange rate or housing price shock, failure of a systemically important financial institution). Therefore, systemic risk measurement could focus primarily on assessing potential losses in both the financial system and the real sector.

- *Amplification and propagation*. In most crises, shocks affect the broader system, including financial institutions, markets, and other sectors (and potentially other countries' financial systems). At that point, systemic risk measurement could focus on amplification mechanisms, such as interconnections between financial institutions, potential fire sales of financial assets, as well as crossborder exposures and the related adverse feedback loops (Figure 3).

Measurement challenges. During the recent global financial crisis, various shock transmission channels reached an unprecedented level of complexity. For example, the range of potential shock transmission channels has broadened considerably, reflecting the greater integration between financial institutions and markets, countries and real sectors (e.g., linkages between public and financial; household or corporate and financial; public and external). As a result, macro-financial linkages and systemic risk are more difficult to measure, given the potential for more complex and unpredictable scenarios, greater scope for nonlinear impacts (e.g., through illiquid markets or institutions), and more unstable correlation structures and behavioral relationships.

B. Key Features of the Toolkit

7. **Focusing on risks at "various" levels**. Available tools may be used to measure systemic risk at different levels of aggregation, including:

- *Individual financial institutions and markets.* For instance, these include (i) market valuation tools to identify price deviations from trend or from levels implied by fundamentals, focusing on assets that are relevant to financial stability (e.g. housing, equity or bond markets); (ii) indicators of risk-taking and stress testing tools to assess the resilience of financial institutions or sovereigns.

- *Risk transmission channels*. Models measuring interactions among financial entities have evolved rapidly in recent years. They are designed to better capture time-varying and nonlinear distress dependences (e.g., during extreme events), or the marginal contributions of individual institutions to systemic risk.

- *The whole financial system and the economy.* Crisis prediction and stress test models aim to capture the risk that the entire financial system is impaired, as well as macro-financial linkages and feedback effects with the real economy. Also, general equilibrium models increasingly integrate financial sector and macroeconomic variables.

8. **Types of risk.** What are the most relevant types of risk that should be monitored and mitigated during each systemic risk phase?

- *Credit risk*. This is a key source of risk in most financial systems. Stress testing methodologies, in particular, have relied on increasingly sophisticated approaches to assess probabilities of default and potential losses if default were to occur (loss-given-default or LGD), especially in relation to various macro factors.

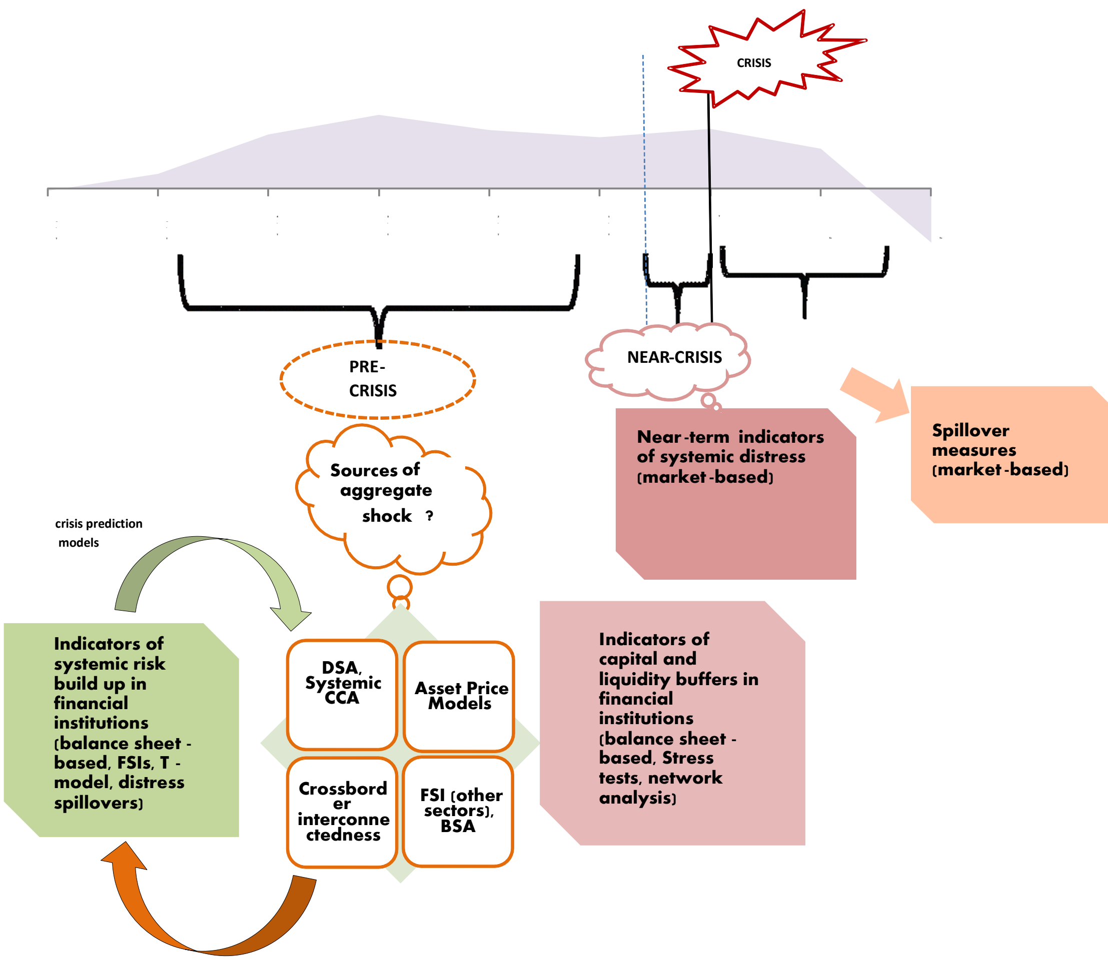
- *Liquidity risk*. Liquidity risk measurement tools have recently been developed to assess not only potential changes to financial institutions' liquidity ratios, but also the interactions between market liquidity (e.g., for thinly traded, illiquid assets) and financial institutions' funding conditions (e.g., through collateralization channels).

- *Market risk*. There is greater familiarity of financial institutions and supervisory authorities with assessing such risks, including through stress testing for interest rate, exchange rate, or asset price shocks. At the systemic level, aggregate measures of market volatility can be used to assess latent vulnerabilities (e.g., to identify periods in which markets are more likely to become more volatile).

9. **Underlying methodology**. Depending on country-specific circumstances, various types of tools and underlying approaches or methodologies are available:

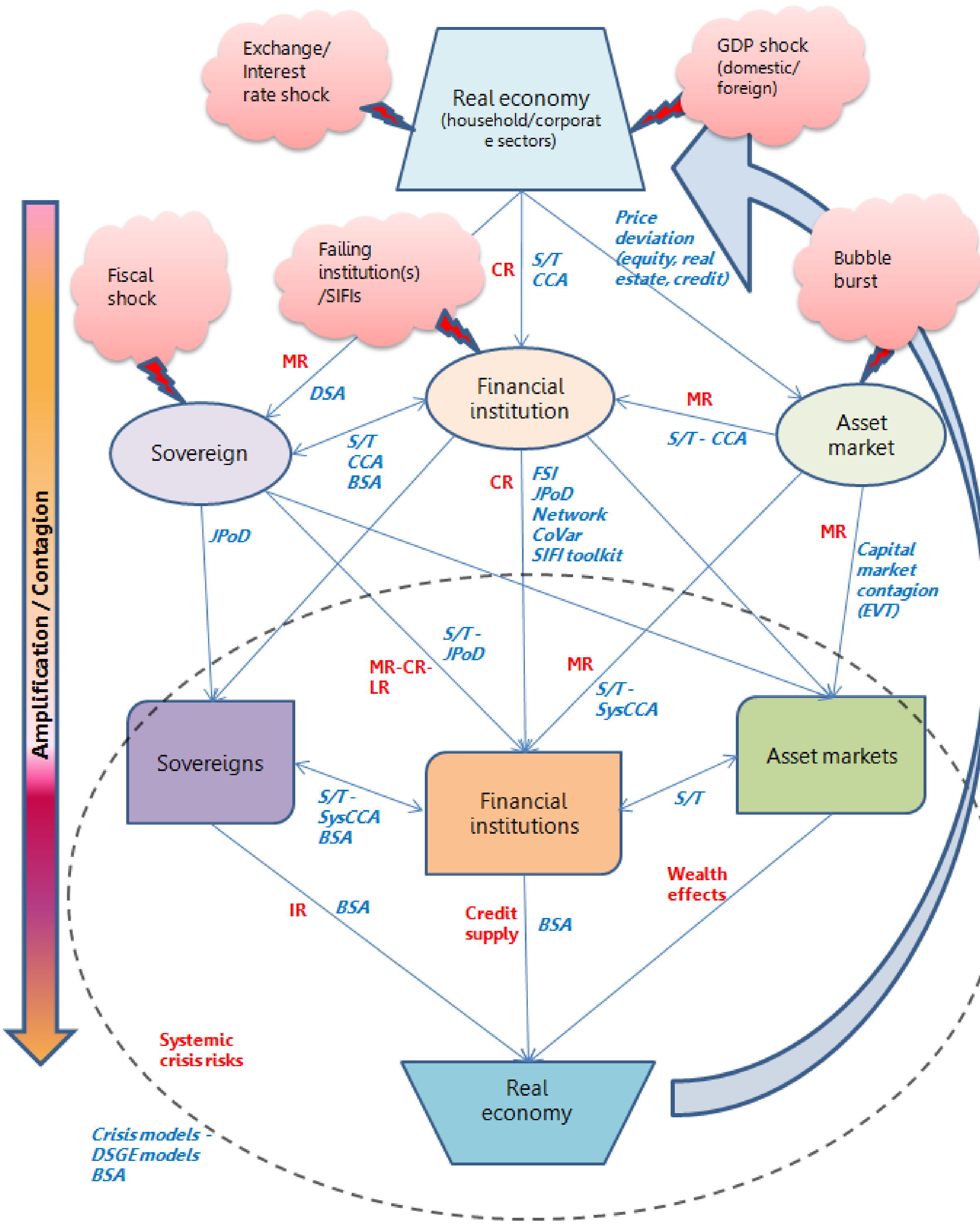
- *Single risk/soundness indicators*. Indicators based on balance sheet data, such as financial soundness indicators (FSIs), are widely available and cover many risk dimensions. However, they tend to be backward-looking and do not account for probabilities of default or correlation structures. Moreover, only some of these indicators can be used as early-warning tools (e.g., indicators of funding structures). Market data can be used to construct complementary indicators for higher-frequency risk monitoring.

Figure 2. Buildup of Systemic Risk: Sources and Channels



Note: FSI stands for Financial Soundness Indicators; T-model: Threshold Model; DSA: Debt Sustainability Analysis; CCA: Contingent Claims Analysis; BSA: Balance Sheet Approach.

Figure 3. Unwinding of Systemic Risk: Sources and Channels



Legend: MR: market risk; IR: Interest rate risk; CR: credit risk; DSA: debt sustainability analysis; S/T: stress testing; CCA: Contingent Claims Analysis; SysCCA: Systemic CCA; FSI: Financial Soundnes indicators; JPoD: Joint probability of Default; EVT: Extreme Value Theory

- *Fundamentals-based models* rely on macroeconomic or balance sheet data to help assess macro-financial linkages (e.g., macro stress testing or network models). By providing vulnerability measures based on actual interconnectedness and exposures, these models may help build a realistic "story." However, they often require long-term data series, assume that parameters and relationships are stable under stressed conditions, and only produce low-frequency risk estimates.

- *Market-based models*. These models uncover information about risks from high-frequency market data and are thus suitable for tracking rapidly-changing conditions of a firm or sector. These approaches are more dynamic, but their capacity to reliably predict financial stress has yet to be firmly established.

- *Hybrid, structural models*. These models estimate the impact of shocks on key financial and real variables (e.g., default probabilities, or credit growth) by integrating balance sheet data and market prices. Examples include the CCA and distance-to-default measures, which compare the market value of an entity's assets to its debt obligations.

10. **Toolkit limitations.** As highlighted above, available tools are very heterogeneous: none is universally applicable to address all aspects of systemic risk, and all are subject to important underlying assumptions, data issues, or "model risk." For instance, as is widely acknowledged, the informational content of market prices may be undermined under certain circumstances (e.g., both during stress and "exuberant" times) or may not capture rising interconnectedness within the financial system. More broadly, and despite ongoing progress in developing and improving the toolkit, efforts to integrate individual tools into a comprehensive and internally-consistent quantitative framework (e.g., across sectors, types of risk, or time horizons) are still in their infancy.

III. Mapping Tools to the Territory—A Practical Approach

11. **This section presents the existing toolkit by addressing six key questions policymakers should ask themselves as they assess systemic risk**. Building on the "Binder" presented in the Appendix, which presents each tool separately, the focus of this section is on the best selections and combinations of tools to address each key question, taking into account the complementarities among tools and their relative strengths and weaknesses.

12. **The proposed sequence of key questions broadly reflects the increasing extent of macro-financial linkages involved in systemic risk monitoring.** Specifically, and for practical purposes, the assumption is that policymakers would start from a 'funnel-view' of the economy, looking at (i) narrow sources of risk within the financial sector (e.g., financial institutions or asset markets), and then turning to (ii) other sources of systemic risks or risk amplification (i.e., in other sectors, the broader economy, or other countries), and finally (iii)

aiming to directly measure the risk and probability of systemic events. In addition to better understanding the underlying sources and severity of crisis risks, such a structured approach may also help policymakers to mitigate systemic risk more effectively, including through a tailored use of specific macroprudential policy tools (IMF, 2011b).

A. Financial Institutions: Is Potentially Excessive Risk Building Up in Financial Institutions?

13. **In order to gauge *risk buildup* at the aggregate level, one should use a combination of balance sheet data that indicate whether financial institutions are taking increasing risk, with potentially systemic impact.** **Financial Soundness Indicators** (**FSIs**) provide a starting point, as they focus primarily on aggregate balance sheet soundness, and may help to identify sources of risk buildup (e.g., FSIs related to sectoral credit growth and leverage).

14. **FSIs are collected comprehensively for many countries and cover a broad range of key risks and buffers, but they tend to be backward-looking indicators.** A similar set of indicators is provided by **Bank Health Assessment Tool (HEAT),** which builds on CAMELS-type financial ratios to derive individual bank indices and can be used to monitor aggregate banking soundness.[3]

15. Complementing FSIs, **Market-Based Probability of Default** measures such as Distance-to-Default (DtD) or Expected Default Frequency (EDF) can be used to assess with higher frequency the probability that individual financial institutions may undergo distress or fail (where relevant market prices—such as equity or CDS prices—are available).

16. **Macro Stress Tests can be used to examine more closely the sources of financial institution vulnerability and to identify specific *weak links* in the system.** Macro stress tests capture a range of risks (e.g., credit, liquidity, and market risks) under "extreme but plausible" (i.e., tail risk) adverse scenarios. They combine these risk factors to evaluate whether financial institutions (both in aggregate and taken individually) have enough capital and liquidity buffers to withstand such scenarios. Key challenges in using stress test models include the calibration of appropriate and internally consistent sets of shocks (across risk factors), and incorporating feedback effects from financial sector problems back into the macroeconomy.

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[3] CAMELS stands for Capital adequacy, Asset quality, Management, Earnings, Liquidity, and Sensitivity to market risk. This concept was developed by banking supervisors in the United States in order to assess the soundness of individual banks.

17. **From a more aggregate and forward-looking perspective, credit growth is often central to the buildup of macro-financial risk, and models such as the Thresholds Model (or T-model) provide rules of thumb on thresholds for changes in credit-to-GDP and its deviation from trend that may signal a systemic financial crisis.** However, the T-model tends to produce thresholds that are fairly low in order not to miss a crisis, and should thus ideally be combined with other tools that tend to yield higher thresholds (e.g., Dell'Ariccia et al, 2012) so as to reduce the chance of a false signal that might lead to a costly policy mistake.

18. **Finally, a number of tools focus on interdependences between financial institutions and assess the risk of *spillovers* among them.** In doing so, these tools may also allow practitioners to identify systemically important institutions. Ideally, policy makers have data on actual interlinkages between financial institutions and systems. In that case, **Network models** can be used to gauge such spillovers triggered by shocks in any one, or more, financial institutions (e.g., the 'weak links' identified above). Such tools can also be applied to aggregate data on cross-country exposures to gauge cross-border spillover risks among financial systems (e.g., based on BIS data). These models provide information on potential spillovers through *direct* exposures. But they do not offer information on how the system might behave during crises, when both *direct and indirect* (e.g., common) exposures come into play.

19. **Complementing the above analyses (or replacing them in the absence of data on direct exposures), models based on market data allow for high-frequency monitoring of the likelihood of spillovers between financial institutions and systemic stress within a short-term horizon (typically less than a year, i.e., near or during crises).** They include **Joint Distress Indicators (JDI)/Financial Institutions Stability Index (FISI)**, **Volatility Spillovers (Diebold-Yilmaz (DY))**, **CoVaR**, **Distress Spillovers (DS)**, **Systemic CCA (SCCA)**. These models and indicators can be used to assess spillovers either under normal (DY) or extreme conditions (JDI, CoVaR, DS, Systemic CCA). Moreover, the **Systemic Liquidity Risk Indicator (SLRI)** provides a coincident indicator of systemic liquidity shortages during market distress. These models do not trace back to the specific risk channels through which such spillovers occur, but some of them help identify which institutions are more systemically important (by estimating individual contributions to systemic stress).

Overall assessment

20. **Overall, when the available toolkit is applied to banks it addresses the above questions well. For example, the complementary tools provide rough rules-of-thumb on when to worry about build-up of risks in the financial sector.** The toolkit identifies the institutions—the weak links—that are vulnerable to adverse shocks in the system; and market-based indicators serve as good near-term indicators of crisis and spillover risks between them. However, many of the above tools apply primarily to bank balance sheets and

interlinkages while, as demonstrated by the current crisis, a range of financial institutions (including recently developed institutions such as Central Counterparties) may also be systemically relevant, requiring a broadened focus of the toolkit and methodologies. Persistent data gaps also hinder analytical efforts to assess nonbank financial institutions. Overall, the combination of tools covers the *impact* of shocks better than their *likelihood*. While significant progress has been achieved, more work is needed to provide firmer guidance for policymakers on risk buildup and on the design and calibration of adverse stress testing scenarios.

B. Asset Prices: Are Asset Prices Growing Too Fast?

21. **Asset Price Models estimate the deviation of an asset market value from its long-term model-based equilibrium, which constitutes a measure of potential for an asset price correction (the assumption being that the larger the misalignment of market prices from fundamental values, the higher the probability of a price correction).** The **Real estate market model**, for instance, provides both (i) direct signals that can be presented in the form of a heat map based on degrees of overvaluation, or (ii) inputs into a model such as the **T- model** that derives crisis signals based on a benchmark country distribution.

22. **More generally, asset price growth features prominently as an early warning signal in Crisis Prediction Models.** Sustained equity price inflation or house price acceleration may reflect financial imbalances building up over time and, when combined with a sharp increase in credit-to-GDP gap and banking sector leverage, may flag a looming domestic banking crisis (**Credit to GDP-Based Crisis Prediction Model**).

23. **However, early warning signals from asset price models are not good predictors of the *timing* of asset price corrections.** Parameters in these models are also less reliable during periods of financial stress, because such parameters are derived (implicitly or explicitly) from fundamental-based equilibrium values based on arbitrage-free asset price models. When such assumptions on free arbitrage do not hold (as in periods of financial stress), the estimated equilibrium values become less reliable.

24. **In addition, asset price models may also help monitor the initial economic *impact* of a potential market correction.** VAR models, for example, can be used to estimate the response of a set of macroeconomic variables (e.g., real GDP, consumption, investment, or inflation) to house price shocks, taking into account household leverage and risk-sharing provisions in mortgage contracts (i.e., a real estate vulnerability index).

25. **Fully-fledged DSGE models are needed to quantify the systemic impact of asset price corrections by incorporating nonlinear effects and feedback loops.** Indeed, the macroeconomic impact of asset price booms and busts depends crucially on the behavior of

the investor base, the dynamics of household leverage, and the likelihood of a credit crunch, as well as feedback effects on the whole financial sector, which can be aided by the construction of structural DSGE models.

Overall assessment

26. **Overall, the available toolkit provides a good set of measures for the size and impact of a potential asset price correction, while its likelihood remains difficult to assess accurately, especially over the near term.** It helps construct a variety of scenarios featuring alternative path-dependent asset price dynamics that support the use of other models, including stress test models (see section A). Yet, it could be better linked to investors' portfolio rebalancing decisions in order to evaluate systemic effects through asset price externalities.

C. Sovereign Risk: How Much is Sovereign Risk a Source of Systemic Risk?

27. **The build-up of sovereign risk can be assessed through Debt Sustainability Analysis (DSA), which typically projects public debt/GDP dynamics over 5 years under baseline and adverse scenarios (e.g., decline in growth rate, sharp rise in interest rate, and sustained increase in primary deficits).** Such an analysis offers a first assessment of sovereign risk buildup, but stress scenarios used in DSA are more akin to sensitivity analysis (their plausibility is not measured). In addition, **Indicators of Fiscal Stress** (IFS) provide a summary measure of the risk of a fiscal crisis over the medium term, based on a coincident indicator of rollover pressures and on a forward-looking index of fiscal stress.

28. **DSA and IFS can be combined with forecasting tools such as Crisis Prediction Models that aim to measure the likelihood of a fiscal crisis (over a one year horizon), by combining asset prices, measures of external and fiscal imbalances, and data on the financial, household, and corporate sectors.** In addition, Schaechter and others (2012) construct a range of indicators to monitor fiscal vulnerability and identify the main underlying fiscal challenges. The choice of indicators is guided by their ability to capture immediate funding pressures, medium and long term funding needs, and risks to the baseline debt dynamics. They can be used to monitor fiscal vulnerabilities in a large set of advanced economies.

29. **In turn, a number of tools can be used to analyze the effect of sovereign risk on financial distress. Macro Stress Tests** may investigate the impact of a decline in government bond prices on financial institutions both directly, through their liquidity and market risk exposures, and indirectly, through a decline in GDP growth (e.g., caused by fiscal consolidation) and increased credit risk. Complementing this approach, **Distress Dependence Model** can also use high-frequency market data to measure the probability of

distress of a financial institution or financial system conditional on sovereign distress. The sovereign **Funding Shock Scenarios** (FSS) can be used along with DSA to do forward-looking analysis to assess sovereign's vulnerability to sudden investor (funding) outflows and banks' potential exposure to sovereign debt.

30. **In addition to the above, some tools can help monitor the potential for negative feedback between financial sector risks and sovereign risk.** For example, there may be concerns that the government balance sheet may not be strong enough to meet contingent liabilities reflecting the existence of (explicit or implicit) public guarantees, leading to increased systemic risk. The **Systemic CCA** allows gauging the impact of such negative feedback effects between sovereign risk and systemic risk.

Overall assessment

31. **Overall, the available tools allow for in-depth assessments of the linkages between sovereign risk and systemic risk, as they cover most risk dimensions, financial institutions, time horizons, and country categories, as well as the impact of shocks and their likelihood**. However, they do not provide clear signals as to whether sovereign risk buildup has reached a critical level that threatens financial stability, or whether it may unleash perverse dynamics leading to a systemic financial crisis and a sovereign debt crisis.

D. Broader Economy: What are the Amplification Channels among Sectors and through the Domestic Economy?

32. **The interconnections and risk exposures among the financial, public, and other sectors can play a key role in magnifying systemic risk.** For instance, they may give rise to concentration risks as well as compounded maturity, currency, and capital structure mismatches. The set of Encouraged **FSIs** provides snapshots of household and corporate leverage and enables comparisons across countries. More detailed analysis of balance sheet data in key sectors (public, private financial, private nonfinancial, household and nonresident) through the **Balance Sheet Approach (BSA)** facilitates cross-sectoral assessments of maturity, currency, and capital structure mismatches. The BSA tool can be used to stress test sectoral positions by assuming shocks related to interest rates and exchange rates. It also provides an indication of the likelihood that an adverse shock may get amplified into a systemic crisis.

33. **Credit growth episodes may also be associated with asset (e.g., real estate) price bubbles, posing a greater threat to financial stability.** As such, **Asset Price** models that provide indicators of such bubbles may usefully complement the above tool (section B). More generally, combinations of credit growth, leverage, and asset price growth, such as in

the **Credit to GDP-Based Crisis Prediction Model,** can be used to estimate relatively well the risk of systemic banking crises about two to three years in advance (section F).

34. **A number of tools help assess more deeply the risks arising from linkages across sectors, including indirectly through second round effects.** For instance, **Asset Price Models** can also help measure the vulnerability of the household and corporate sectors to asset price corrections, as well as the broader spillover effects on GDP (section B), although they do not take into account feedback loops through the impact of lower growth on asset price levels. As noted above, **Debt Sustainability Analysis** (DSA) also examines the impact of real economy, market, and financial system shocks on sovereign risk (Section C), and can be combined with the **Systemic Contingent Claims Approach** (SCCA) to obtain complementary and more forward-looking estimates of these impacts (sections A and C). **Macro Stress Tests** assess the impact of a wide range of risks and adverse scenarios on financial institutions, individually or in aggregate. Importantly, however, feedback effects on the economy, including through credit supply conditions, are not appropriately covered in stress test models at this point.

35. **Beyond sector-specific linkages, some tools combine cross-sectoral interdependences to assess spillovers of systemic, economy-wide relevance.** In particular, the **GDP at Risk** model forecasts systemic real and financial sector tail risks using time series indicators of financial and real activity. This complex model may not be overly user-friendly, but it captures the dynamic responses of systemic risk indicators to structural shocks, and may provide useful early warnings of systemic events. Moreover, **DSGE models** provide an in-depth understanding of the interactions and shock transmission across sectors and with the broader economy, including by capturing inter-sectoral and macroeconomic dynamics (e.g., cyclical fluctuations). However, these models are particularly difficult to calibrate and interpret.

Overall assessment

36. **Overall, the available toolkit addresses several key inter-sectoral linkages and related risk buildup.** However, further efforts are needed to combine these approaches into integrated, economy-wide measures of systemic risk. In particular, there is a need to incorporate feedback and second-round effects across sectors in order to fully capture sectoral risk transfers and enhance the spillover analysis. One example is the gap in stress tests on links between financial sector stress and credit supply conditions, the impact of these conditions on the real economy, and feedback effects on financial sector stress.

E. Cross-Border Linkages: What are the Amplification Channels through Cross-Border Spillovers?

37. Encouraged **FSIs** related to geographical distribution of loans and foreign-currency denominated liabilities are a starting point for the analysis of cross-border exposures as they may indicate that, on aggregate, a financial system is exposed to credit risk from certain countries or is vulnerable to funding risk from cross-border sources.

38. **A more forward-looking perspective on the buildup of cross-border spillover risks is provided by balance of payments and international investment position data, such as data on capital inflows and outflows, and on changes in banks' foreign liabilities.** These can be combined in the **T-model** to obtain threshold-based signals of a potential financial crisis.

39. **Macro Stress Tests also increasingly take into account cross-border linkages in identifying adverse scenarios (as relevant in each country case).** Indeed, in order to assess domestic financial institutions' solvency and liquidity positions comprehensively, they need to capture a range of risks (e.g., foreign credit, liquidity, foreign sovereign and foreign market risks) arising from cross-border exposures and related risks and scenarios in other jurisdictions.

40. **In order to assess more deeply and dynamically the interdependences that may generate cross-border spillovers among financial systems or institutions, policymakers should ideally have access to the necessary data on actual interlinkages between such financial institutions and systems.** In this case, network models can be used to gauge such spillovers due to shocks in any one, or more, financial institutions (e.g., the G-SIFIs) or among financial systems. Specifically, BIS data can be used to run the two network models: the **Cross-Border Network model** can be used to calculate different types of connections (first-round impact) between financial systems and estimate the probability of a domestic financial crisis, while the **Cross-Border Banking Contagion model** can be used to run a network analysis (including multiple-round spillovers) of solvency and funding risk from each financial system to the country. These models provide information on potential spillovers through *direct* exposures, but they do not offer information on how the system might behave during crises, when both *direct and indirect* (including common) exposures come into play.

41. In the absence of full cross-exposure data, or in order to complement the above analyses, spillover models based on market data—such as **JDI**, **Returns Spillovers (or Diebold-Yilmaz, DY)**, **Distress Spillovers (DS)**, **Systemic CCA (SCCA)**—can be used to assess potential reactions and spillovers between financial institutions across borders, either under normal (DY) or extreme conditions (JDI, DS, SCCA).

Overall assessment

42. **The available tools tend to capture somewhat better the *impact* of cross-border shocks than their *likelihood*.** However, data limitations with regard to cross-border exposures, especially among individual institutions (e.g., G-SIFIs) and with other sectors in foreign countries, remain a serious obstacle to in-depth analyses of cross-border contagion risks.

F. Crisis Risks: What is the Probability of a Systemic Crisis?

43. **Several tools extract information from asset prices to estimate the probability of a crisis occurring within a certain time interval**.[4] Specifically, the **Systemic CCA** and **JDI** can be directly applied to estimate the probability that a certain number of institutions will jointly fail in the near-term, thereby triggering financial instability. The systemic CCA can also indicate the probability that the aggregate losses of the financial system will be above a certain specified amount. Alternatively, the **Regime Switching Model** estimates the probability that financial markets will enter into a state of high volatility or "crisis." Finally, the **SLRI model** can be used to assess the probability of systemic liquidity pressures in capital markets.

44. **However, while the above tools (relying primarily on asset price data) generally signal crisis events with a relatively high degree of confidence, they offer only limited lead time (e.g., a month or, at most, a year).** This may not be sufficient from a policymaker's perspective. In addition, they are subject to increased error risks when markets incorrectly price risks, for example in the case of illiquid markets.

45. **In order to obtain measures of crisis probability with longer lead time, policymakers should also rely on techniques that combine information on aggregate credit growth with other macroeconomic or balance sheet indicators.** In particular, the **Crisis Prediction Model** yields direct measures of the probability of a financial crisis associated with excessive credit growth or private sector leverage (among other variables). And the **T-model** can signal the increased likelihood of crisis materialization, without providing numeric estimates for the probability of such events. However, these techniques are subject to the typical limitations associated with reduced-form econometric models, and

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[4] As noted, the application of various tools to estimate the likelihood of crises requires defining ex-ante what constitutes a crisis. For instance, bank regulators and supervisors may be interested in assessing the probability that a certain number of banks will fail at the same time, or that their joint losses will be above a certain threshold. Investors may be more concerned about the probability that sovereign debt or real estate prices will fall below a certain level instead.

may in particular under-estimate crisis probabilities (relative to the actual occurrence of systemic events).

46. **DSGE models combine a broad range of variables, including output, consumption or asset prices, and provide an in-depth understanding of macro-financial linkages and how these could behave under stressed conditions, or in reaction to particular policy actions.** In addition, the specification and estimation of these models may not depend on high-frequency information contained in asset prices, allowing them to overcome some of the problems with the other techniques discussed above. However, they rely on numerous assumptions about the structure of the economy, increasing the likelihood of misspecification errors.

Overall Assessment

47. **While combining available tools to estimate the likelihood of a crisis can be valuable to policymakers, these tools taken individually are subject to important limitations.** The ability of asset-price-based models to accurately estimate crisis probability declines precipitously with time. Structural models overcome these limitations, but at the cost of misspecification errors, which are also pervasive in reduced-form statistical techniques. Therefore, DSGE and Crisis Prediction models can be applied to cross-check whether contemporaneous increases in crisis probability emanating from financial market data are corroborated by longer term measures of risk build-up. Conversely, authorities should use models based on high-frequency asset price data to monitor the intensification of pressures if structural or econometric models have indicated, in the past, the increased probability of stress.

IV. Sample Country Case Study

48. **This section aims to provide a concrete illustration of the use of the systemic risk monitoring toolkit in a fictitious country case** (Figure 4). The diagrammatic presentation of the key questions from the previous section provides a practical guide to policy makers in the form of a systemic risk monitoring dashboard that can be tailored to each country's specific circumstances and key risk factors at a given point in time. The illustration uses an unidentified advanced country as an example.

49. **The systemic risk dashboard combines (complementary) tools and allows to construct a comprehensive "story" about a country's key systemic risk at a point in time.** The sample dashboard for country X, at end-2007, addresses the six questions successively in six chart panels, and provides a summary of the key observations under each panel as follows:

- *Panel A: Credit growth has slowed down and banking stability is falling fast and below 2003 levels at end-2007. Systemic risk is starting to materialize.*
  This panel combines a low-frequency indicator of credit growth (change in the credit-to-GDP ratio) with a high frequency, market-based indicator of systemic risk in the banking system (Distance to Default). Together, this combination provides insights on the particular phase of systemic risk among financial institutions. Consumer credit growth has fallen below 2001 levels. The market-price based measure shows that banking sector vulnerabilities are heightened.

- *Panel B: There are mixed signals from asset prices: house prices are falling (red) for Country X and for countries to which Country X's banks are exposed. However, not all equity market models are showing misalignments for Country X and its trading partners.*
  This panel combines heat-maps of house prices and equity prices to detect signs of overheating in asset markets. The indicators are calculated for many countries, putting Country X's situation in a cross-country perspective. Together with Panel A, it seems that financial sector difficulties could be increasing as of end-2007.

- *Panel C*: *There are clear signals that fiscal risks are increasing, especially from financial sector-related contingent liabilities.*
  This panel assesses sovereign-bank linkages through public contingent liabilities (Debt Sustainability Analysis) and potential changes in banks' holdings of sovereign debt under stress scenarios. Debt Sustainability Analysis shows that the debt/GDP could rise substantially should contingent liabilities materialize. Such liabilities could be related to the financial sector. The Sovereign Funding Shock Scenarios (FSS) show that under certain scenarios, bank holdings of public debt may increase sharply, leading to stronger sovereign-bank linkages in the country.

- *Panel D: There is limited evidence that financial sector shocks are spilling over into the real sector at this stage, although spillover risk within financial institutions is slowly rising.*
  This panel focuses on risk amplification across sectors and the economy (GDP-at-Risk and Financial Stability-at-Risk), and adverse feedback loops between contingent public liabilities and banking sector distress (Systemic Contingent Claims Analysis). The Financial Stability at Risk (FSaR) and GDP at Risk (GDPaR) are the worst possible realization, at 5 percent probability, of quarterly growth in real GDP and in the equity returns of a large portfolio of financial firms, respectively. At end-2007, it is unclear from the GDPaR that intensified financial sector stress could spillover to GDP growth. However, the Systemic Contingent Claims Analysis confirms that sovereign contingent liabilities are increasing.

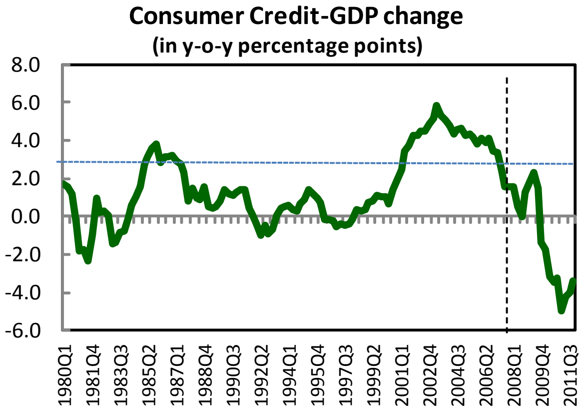
- *Panel E: Country X continues to be strongly connected to the rest of the world, both in terms of actual cross-border balance sheet linkages of banks and potential spillover risks from market contagion.*
  This panel illustrates cross-border spillover and contagion risks from two complementary perspectives: Joint Distress Indicators based on market-prices, and Network Analysis using BIS data. Network Analysis of bilateral cross-border banking claims shows that the vulnerability of X from countries A and B are very high. Market-based Joint Distress Indicators are showing a rise in spillover risks between X and four other countries.

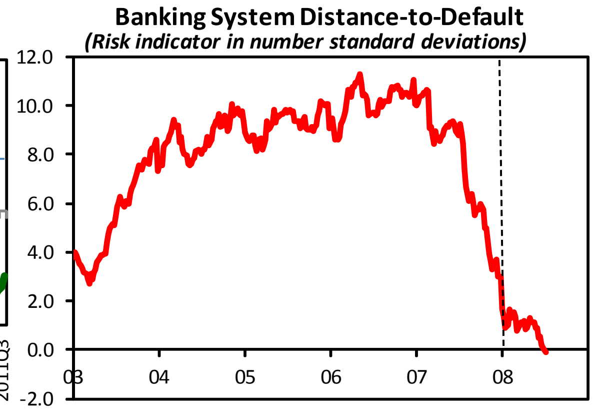
- *Panel F: The estimated likelihood of a systemic crisis has increased, but is still small.*
  This panel directly estimates the likelihood of a systemic crisis, either a banking sector crisis or a broader economic crisis, based on complementary probability models. The credit-based banking crisis model shows an uptick in crisis probability, and so does a more general crisis prediction model.

Figure 4. Systemic Risk Dashboard for a Fictitious Country X at end-2007

Summary Assessment: *Overall, the set of tools suggests that Country X is about to face intensified financial stress, although the extent of the crisis and its implications for economic growth are unclear. From the dashboard presented below, a policymaker could formulate a first assessment of key sources of systemic risks. In this example, Country X is facing financial stresses that could have a systemic impact in the financial sector. Sovereign risk is heightened by contingent liabilities. Contagion risks from financial sector problems in partner countries would have a large domestic impact. Among asset market indicators, house prices are clearly decelerating, while consumer credit growth has slowed along with a sharp drop in banking stability indicators. However, amplification channels through the broader financial system and domestic economy, while uncertain, do not yet seem to play a significant role. Also, there is no strong signal that a full-fledged financial crisis is about to materialize, even though its probability is rising.*

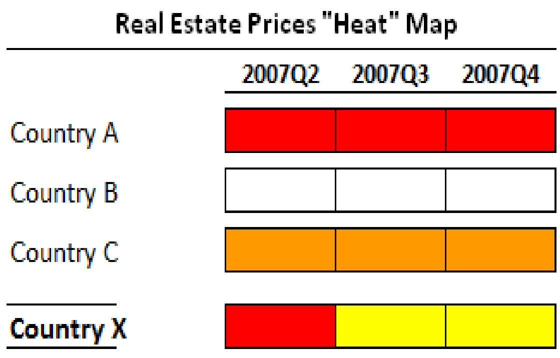
A. Is excessive risk building up in financial institutions?





Summary: Credit growth has slowed down and banking stability is falling fast, and below 2003 levels at end-2007. Systemic risk is starting to unwind.

B. Are asset prices growing too fast?

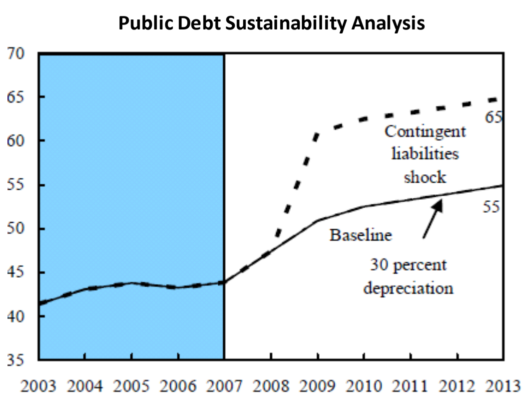


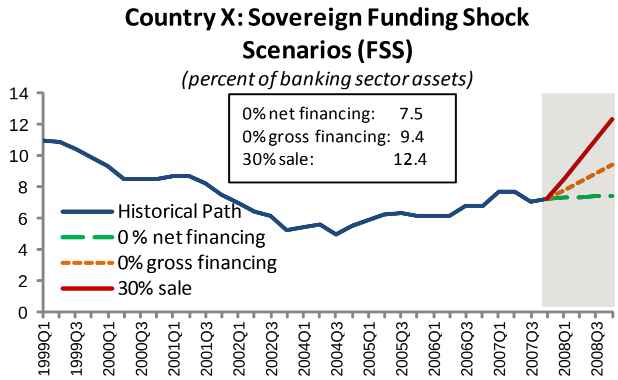
Equity Market Misalignments
Deviation Between Market and Model Prices
Dec, 2007

	Dividend Discount Model	Arbitrage Pricing Theory (APT) Model Local	APT Global
Country A	-3.2	-0.1	-1.5
Country J	-2.3	1.3	-1.4
Country N	-4.1	3.8	-1.2
Country X	-1.7	1.0	-1.4

Summary: There are mixed signals from asset markets at end-2007.

C. How much is sovereign risk a source of systemic risk?

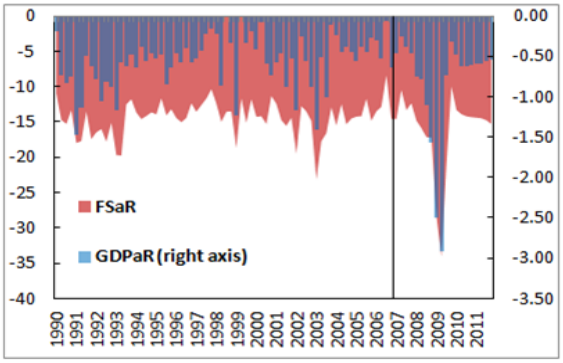




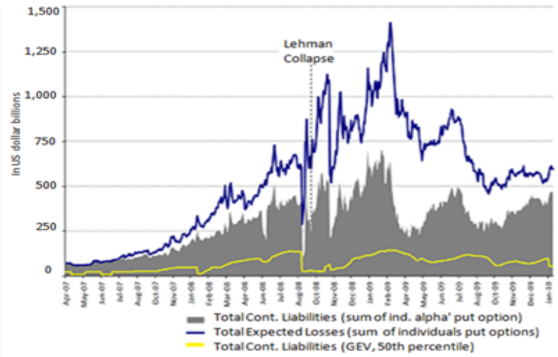
Summary:There are clear signals that fiscal risk are increasing, especially from financial sector-related contingent liabilities.

D. What are the amplification channels among sectors and through the broader domestic economy?

GDP-at-Risk and Financial Stability-at-Risk

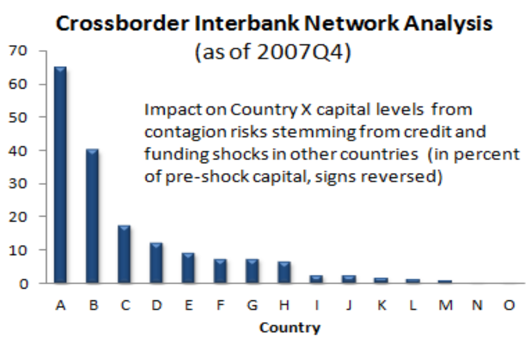


Systemic Contingent Claims Analysis

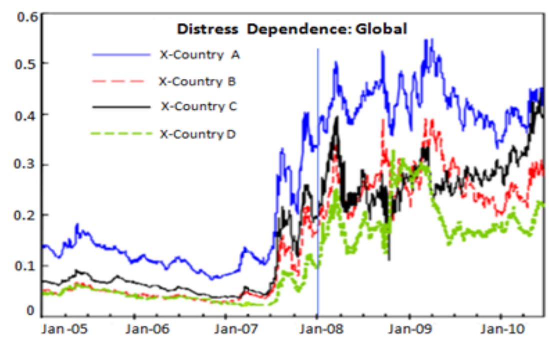


Summary: There is limited evidence that financial sector shocks are spilling over into the real sector at this stage, although spillover risk within financial institutions is slowly rising.

E. What are the amplification channels through crossborder spillovers?



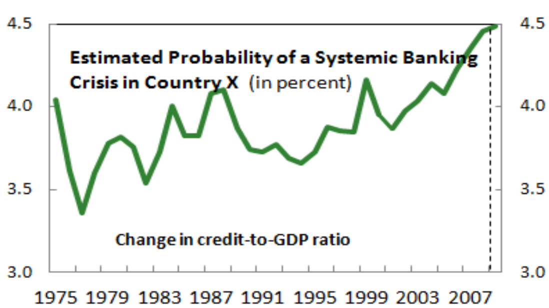
Joint Distress Indicators



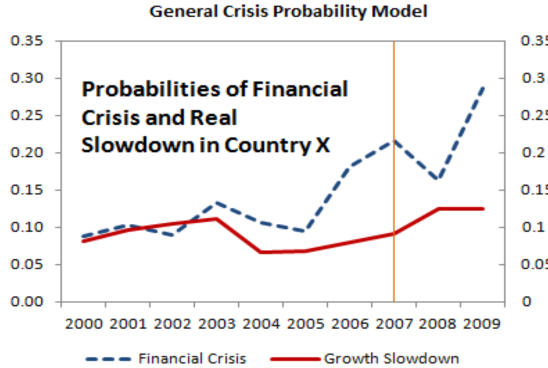
Summary: Country X continues to be strongly connected to the rest of the world, both in terms of actual balance sheet linkages of banks and potential spillover risks from market contagion.

F. What is the probability of a systemic financial crisis?

Credit-Based Crisis Probability Model



General Crisis Probability Model



Summary: The estimated likelihood of a systemic crisis has increased, but is still small.

V. KEY FINDINGS AND OPERATIONAL IMPLICATIONS

50. **On balance, several dimensions of systemic risk are covered well by the toolkit.** Tools exist to address most of the key sources of shocks and transmission channels, and appear to do so relatively well along the following dimensions:

- *Impact* of shocks rather than the *likelihood* of systemic events.
- *Long-term buildup* of balance sheet vulnerabilities.
- *Spillovers* across financial entities.
- *Cross border contagion* between banking systems.

51. **A number of operational implications emerge from the above discussion**:

- *Tools should be combined to exploit their complementarities***.** Such complementarities help to cross check and confirm the materiality of sources of systemic risk stemming from domestic macro-financial imbalances (e.g. credit boom, asset price bubble, unsustainable public debt) and cross-border linkages, or individual institution exposures (e.g. size, leverage, interconnectedness). Therefore, they help practitioners to avoid overreacting to a single signal, or being lulled into a false sense of security.
- *The selection of tools should be country-specific*. Not all tools are applicable or relevant in all country circumstances (e.g., due to specific data requirements).
- *The use of various tools should reflect the typical phases of systemic risk*:
    - The slow buildup of risk (e.g., through combinations of balance-sheet and slow-moving indicators).
    - The identification of weak points and potential adverse shocks (e.g., stress tests to detect weak financial institutions, asset price deviation from fundamentals).
    - The fast unfolding of crises, including through amplification mechanisms (e.g., high frequency market-based spillover measures).
- *Longstanding data gaps remain an obstacle* to assessing key systemic risk components, including interlinkages and common exposures, which is increasingly problematic in light of the growing complexity of financial crises.

52. **However, from the perspective of guiding macroprudential policy, the systemic risk monitoring toolkit is incomplete.** The systemic risk monitoring framework is work in progress in a number of key dimensions. Tools exist to assess most sectors and levels of aggregation, but they provide only partial coverage of potential risks and only tentative signals on the likelihood and impact of systemic risk events. As such, they may not provide sufficient comfort to policymakers. Indeed, a number of practical and theoretical roadblocks remain that currently limit our capacity to measure systemic risk in comprehensive and accurate ways:

- *Early warning*. The forward-looking properties of systemic risk measures are generally weak, even though some measures appear relatively promising, such as combinations of credit-to-GDP and asset valuation measures, and certain high-frequency market-based indicators.

- *Thresholds.* Policymakers need clear and reliable signals indicating when to "worry" and when to take action, and allowing them to monitor the impact of such action over time. Despite recent progress, further work is needed in this area.

- *System's behavior*. The capacity to model aggregate agent behaviors is limited in several areas, such as banks' approaches to internalizing the materialization or increasing likelihood of systemic risk, potential reverse feedbacks and multi-round effects (i.e., "perfect storms"), and nonlinear risk correlations during periods of financial distress.

53. **More broadly, the incomplete nature of the toolkit highlights the need to avoid mechanistic, or narrow, approaches to systemic risk monitoring.** The successful use of quantitative diagnostic tools depends critically on the use of sound judgment. Policymakers should not be led to believe that some quantitative approaches (e.g., stress tests or crisis prediction models) are "all-in-one" tools for systemic risk assessments. Indeed, such assessments should bring together not only various types of tools, but also qualitative information, based on market intelligence or on a thorough analysis of a country's macroeconomic and financial stability frameworks.

Table 1. Characteristics of Different Systemic Risk Monitoring Tools—A Summary

Tools	Coverage			Data Requirements		Applicability across Countries			Applicability across Questions						Additional Characteristics					Form of Publication	Main Reference
	Institutions	Markets	Sectors	Frequency	Type of Data	Low Income	Emerging	Advanced	A	B	C	D	E	F	Thresholds	Early Warning	Impact of crisis	Amplification	Spillovers/Interconnected		
1. Conditional Value at Risk (CoVaR)	Y		Financial	High	Asset prices and balance sheet data	Limited	Y	Y	Y				Y		Y	Y	Y		Y	W	Adrian & Brunnermeier, 2010
2. Joint Distress Indicators	Y		Financial	High	Asset prices		Limited	Y	Y				Y	Y		Y	Y		Y	W	Segoviano and Goodhart, 2009
3. Returns Spillovers	Y		Financial	High	Asset prices	Limited	Y	Y	Y				Y		Y	Y	Y		Y	P	Diebold and Yilmaz, 2009
4. Distress Spillovers	Y	Y	Financial	High	Asset prices	Limited	Y	Y	Y		Y		Y			Y	Y		Y	P	Chan-Lau, Mitra and Ong, 2009
5. Market-Based Probability of Default	Y		Financial and corporate	High	Asset prices and balance sheet data	Limited	Y	Y	Y							Y				O	Kealhofer, 2003
6. Debt Sustainablity Analysis			External and public	Low	BoP and fiscal data	Y	Y	Y			Y	Y			Y		Y			F	IMF, 2002 and 2003
7. Indicators of Fiscal Stress			Fiscal	Low	Fiscal	Y	Y	Y		Y					Y	Y					Baldacci, McHugh and Petrova , 2011
8. Sovereign Funding Shock Scenarios		Y	Financial and public	Medium	Investor base and bank asset		Y	Y	Y		Y				Y		Y			W	Arslanalp and Tsuda, 2012
9. Asset Price Models		Y		Medium	Asset prices and cash flow data	Limited	Limited	Y	Y	Y		Y			Y	Y		Y		F	IMF-FSB, 2010
10. Balance Sheet Approach			All main sectors	Low	Sectoral balance sheet data	Y	Y	Y			Y	Y				Y		Y	Y	W	Allen, Rosenberg, Keller et al, 2002
11. Systemic Contingent Claims Analysis	Y		Financial	High	Asset prices and balance sheet data	Limited	Y	Y	Y		Y	Y	Y	Y		Y	Y		Y	P	Gray and Jobst, 2011

Tools	Coverage			Data Requirements		Applicability across Countries			Applicability across Questions						Additional Characteristics					Form of Publication	Main Reference
	Institutions	Markets	Sectors	Frequency	Type of Data	Low Income	Emerging	Advanced	A	B	C	D	E	F	Thresholds	Early Warning	Impact of crisis	Amplification	Spillovers/Interconnected		
12. Cross-Border Interconectedness	Y		Banking	Low	Cross-border banking exposure and balance sheet data	Limited	Y	Y	Y				Y		Y	Y	Y		Y	W	Cihak, Munoz and Scuzzarella, 2011
13. Cross-Border Network Contagion	Y		Banking	Low	Cross-border banking exposure and balance sheet data	Limited	Y	Y	Y				Y				Y		Y	W	Espinosa-Vega and Sole, 2010
14. Systemic Liquidity Risk Indicator	Y		Financial	High	Asset prices and balance sheet data		Limited	Y		Y				Y			Y			W	Severo, 2012
15. Regime switching		Y	Financial	high	Asset prices	Y	Y	Y	Y					Y	Y	Y	Y			W	González-Hermosillo and Hesse,
16. Financial Soundness Indicators	Y	Y	Financial, corporate and household	Low	Cash flow and balance sheet data	Y	Y	Y	Y			Y	Y			Y				F	IMF, 2006
17. Bank HEalth Assessment Tool (HEAT)	Y		Financial	Low	Balance sheet	Y	Y	Y	Y							Y				W	Ong, Jeasakul and Kwoh, 2012
18. Thresholds Model			Financial	Low	Macroeconomic data	Y	Y	Y	Y	Y			Y	Y	Y	Y		Y		F	Borio and Drehmann, 2009
19. Macro Stress Tests	Y		Financial		Asset prices and balance sheet data	Limited	Y	Y	Y		Y	Y	Y				Y	Y		F	Moretti, Stolz and Swinburne, 2008
20. GDP at Risk			Real, financial	Low	Asset prices and macroeconomic data	Y	Y	Y	Y			Y			Y	Y	Y	Y		P	De Nicolo and Lucchetta, 2010
21. Credit to GDP-Based Crisis Prediction Model			Financial	Low	Macroeconomic data	Limited	Y	Y	Y	Y	Y			Y	Y	Y				W	Lund-Jensen, 2012
22. Crisis Prediction Model			Financial and public	Low	Macroeconomic data	Limited	Y	Y	Y	Y	Y			Y	Y	Y				F	IMF-FSB, 2010
23. DSGE Model			Corporate and household	Low	Macroeconomic data	Y	Y	Y		Y		Y		Y			Y	Y		F	Benes and others, 2010

Note: "Y" implies that the indicator can be used for the categories; a blank implies the indicator cannot, as yet, be used for the categories unless otherwise noted.
Under Publications, P=Published in peer reviewed journal/book; W= Working Paper; F=IMF policy and other multilateral surveillance papers; O=Other publications available online.

Appendix. Tools Binder

TOOLS FOR SYSTEMIC RISK MONITORING

February 2013

Contents Page

I. CONDITIONAL VALUE-AT-RISK (COVAR)

The CoVaR uses market data to assess the contribution of an individual financial institution to systemic risk. It is easy to use/update and has good in-sample forecasting properties for systemic stress, but does not identify the underlying spillover channels.

Tool Snapshot

Attributes	Description
Summary properties	
"Systemic reach"	Aggregation of core financial institutions (listed)
Forward-looking Properties	Good in-sample forecasting abilities for systemic stress in the US and Euro Area financial institutions
Ease of use	Easy to use and update
Identification of linkages	Not identified
Likelihood (PD) or impact (LGD)?	LGD
Coverage	
Sectors/Institutions	All financial institutions with high-frequency market data that provide various measures of return (e.g., equity prices, CDS spread, or Market Value of Assets).
Types of risk	Contribution of one institution to system-wide distress.
Interpretation	
Main output	The expected loss in the financial system conditional on one or many financial institutions being in distress (left-tail outcome).
Other outputs	Total expected loss in the financial system conditional on one or more financial institutions being in distress; the vulnerability of an institution to system-wide risk ("Exposure CoVaR").
Thresholds	Yes (e.g., 7.2 percent returns on market value of assets for US institutions; 0.9-1.8 for Euro Area institutions signaling 2007-2009 crisis phase).
Time horizon	Good for predicting near-term materialization of financial system-wide stress.
Data requirements	High frequency market-based financial time series; flexible series of returns, but limited to institutions with market data.
Reference	Main: Adrian and Brunnermeier, 2010; Users: Arsov and others, 2013.

Methodology

Quantile regressions are used to derive time-varying CoVaR. Specifically, the measure of contribution of an institution to systemic risk is ΔCoVaR: the difference between the VaR of the financial system conditional on the distress of a particular financial institution *i* and the VaR of the financial system conditional on the median state of the institution *i*.

Quantile regressions—the 5th and the 50th–of the weekly returns (growth in market value of assets), of institution I, X^i_t, and the system, X^{system}_t are estimated, conditional on state variables, M_{t-1}. The Libor-OIS spread and the weekly change in the yield curve (defined as the spread between the 10-year Treasury bond yield and the 3-month Treasury bill yield) are used in M.

$$X_t^i = \alpha^i + \gamma^i M_{t-1} + \varepsilon_t^i,$$
$$X_t^{system} = \alpha^{system|i} + \beta^{system|i} X_t^i + \gamma^{system|i} M_{t-1} + \varepsilon_t^{system|i}$$

The predicted/fitted values are used to derive the following at q=5% and q=50%:

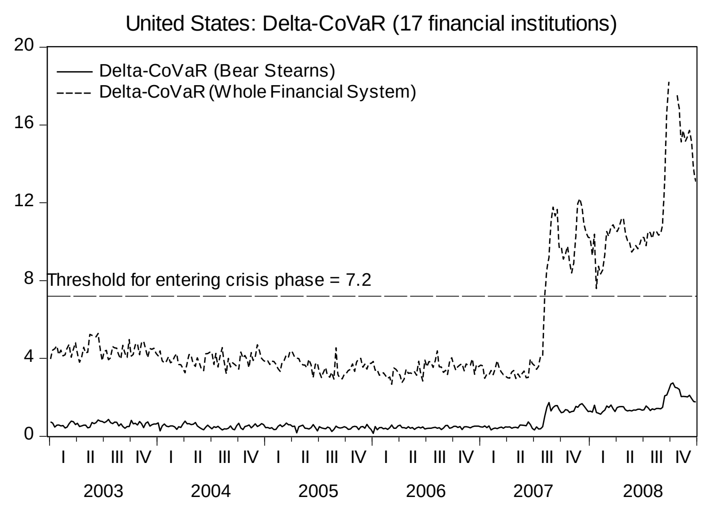
$$VaR_t^i(q) \equiv \hat{X}_t^i = \hat{\alpha}_q^i + \hat{\gamma}_q^i M_{t-1},$$
$$CoVaR_t^i(q) \equiv \hat{X}_t^{system} = \hat{\alpha}^{system|i} + \hat{\beta}^{system|i} VaR_t^i(q) + \hat{\gamma}^{system|i} M_{t-1}.$$

Finally, the ΔCoVaR of each institution is simply:

$$\begin{aligned}\Delta CoVaR_t^i(5\%) &= CoVaR_t^i(5\%) - CoVaR_t^i(50\%) \\ &= \hat{\beta}^{system|i}(VaR_t^i(5\%) - VaR_t^i(50\%))\end{aligned}$$

Example

Country/Financial Institutions: 17 U.S. financial institutions covering commercial and investment banks. The chart shows the time-varying ΔCoVaR of the financial system and the systemic contribution of Bear Stearns to overall stress. A value of 7.2 represents the loss-rate in the system when a portfolio of firms moves from their median state to a distress-state.



Source: Arsov and others (2013).

II. JOINT DISTRESS INDICATORS

The set of Joint Distress Indicators (JDI) includes a time-varying measure of joint probability of distress (JPoD) between financial institutions or sovereigns, with nonlinear distress dependence. These indicators can be used to construct a Financial Institutions Stability Index (FISI) reflecting the expected number of financial institutions (FIs) becoming distressed given that at least one FI has become distressed. It can also be used to assess banks' inter-linkages by computing pair-wise conditional probabilities of distress. The JDI provides complementary perspectives of systemic risk and FIs' exposure and contribution to systemic risk.

Tool Snapshot

Attributes	Description
Summary properties	
"Systemic reach"	Measures distress of a financial institution or system conditional on a specific financial institutions or sovereign being in distress
Forward-looking Properties	Near-coincident indicator of distress. Signal of near-term jumps in conditional joint distress.
Ease of use	Not easy to use and update unless using the econometrics code (available on request).
Identification of linkages	It estimates the time varying distress dependence and contributions to contagion and systemic risk of each financial institution or sovereigns Further, the Distress Dependence Matrix provides insights into inter-linkages between institutions.
Likelihood (PD) or impact (LGD)	Conditional and unconditional PD.
Coverage	
Sectors/Institutions	Banks, nonbank financial institutions, and sovereigns.
Types of risk	Spillover risk during distress, i.e., expected large losses or possible default. It covers credit,
Interpretation	
Main output	FISI, JPoD, Distress Dependence Matrix (DiDe), and Probability of Cascade Effects (PCE)
Other outputs	Spillover coefficient (SC) and Toxicity Index (TI).
Thresholds	No specific thresholds. When FISI=1, asymptotic independence among FIs; as the value of BSI increases, bank linkages rise.
Time horizon	Coincident indicator of interconnectedness.
Data requirements	CDS spreads, equity prices, or out-of-the-money option prices, bond spreads, interbank financing cost spreads.
Reference	Segoviano and Goodhart, 2009.

Methodology

A distress dependence measure is based on estimating the Consistent Information Multivariate Density Optimizing (CIMDO)-density of the banking system that captures time-varying linear and nonlinear distress dependence among banks. Denote by p(x,y,r) the CIMDO-density of the financial system defined by FIs X, Y, and R.

The Joint Probability of Distress (JPoD) is estimated by integrating the density function over the tail of the distribution. It is used as an input to construct all banking stability measures.

$$JPoD = \iiint p(x,y,r)dxdydr$$

The FISI reflects the expected number of FIs becoming distressed given that at least one FI has become distressed. Denote by x_d^x, x_d^y, x_d^r the distress threshold of return for FIs x, y, and r, respectively. The FISI is defined as: $FISI = \dfrac{P\left(X \geq x_d^x\right)+P\left(Y \geq x_d^y\right)+P\left(R \geq x_d^r\right)}{1-P\left(X < x_d^x, Y < x_d^y, R < x_d^r\right)}$

Bank interlinkages are assessed by estimating the following conditional probabilities. First, the probability of distress of bank X conditional on bank Y being distressed is computed. This measure captures X's exposure to bank Y's distress: $P\left(X \geq x_d^x \middle| Y \geq x_d^y\right) = \dfrac{P\left(X \geq x_d^x, Y \geq x_d^y\right)}{P\left(Y \geq x_d^y\right)}$

Second, the PCE is the probability that at least one FI becomes distressed given that X has become distressed. This measure reflects X's systemic importance in the banking system:

$$PCE_X = P\left(Y \middle| X\right) + P\left(R \middle| X\right) - P\left(Y \cap R \middle| X\right)$$

Example

This analysis has been applied to estimate the stability of a set of six Swedish banks using daily CDS spreads over January 2007–October 2010. Figure 1 graphs the evolution of FISI over time. Table 1 shows the PCE conditional on column i FI defaulting computed on a pre-crisis date and at the event of collapse of Lehman Brothers. Table 2 shows the distress dependence matrix, i.e., the conditional probability of row i's FI defaulting given column j's default, also computed on September 15, 2008.

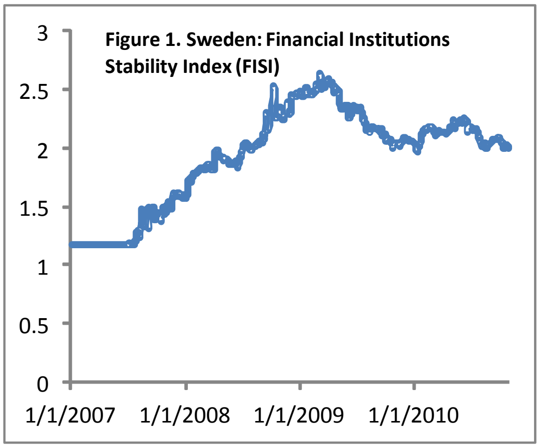


Table 1. Probability of Cascade Effects (PCE) from default of an FI

	SEB	Handels banken	Swed-bank	Nordea	DnB Nor	Danske
1/1/2007	0.32	0.29	0.21	0.37	0.21	0.21
9/15/2008	0.85	0.87	0.69	0.87	0.79	0.74

Table 2--Distress Dependence Matrix (DiDe)

9/15/2008	SEB	Handels banken	Swed-bank	Nordea	DnB Nor	Danske
SEB	1	0.65	0.53	0.62	0.54	0.49
Handelsbanken	0.39	1	0.29	0.48	0.40	0.33
Swed-bank	0.64	0.58	1	0.59	0.50	0.50
Nordea	0.48	0.61	0.37	1	0.49	0.43
DnB Nor	0.34	0.42	0.26	0.40	1	0.37
Danske	0.36	0.41	0.30	0.41	0.44	1

Source: IMF Staff estimates.

III. Returns Spillovers

The spillover measure suggested by Diebold and Yilmaz (2009), DY, is a time-varying indicator of outward returns-spillovers of institutions—the contribution of one institution to systemic risk. The indicator uses market data on returns (CDS spreads or equity prices) to estimate average (not 'extreme') contributions and is easy to use/update. It also has good in-sample forecasting properties for systemic stress, but does not identify the underlying spillover channels, except those between institutions.

Tool Snapshot

Attributes	Description
Summary properties	
"Systemic reach"	Aggregation of core financial institutions (listed)
Forward-looking Properties	Good in-sample forecasting abilities for systemic stress in the US and Euro Area financial institutions
Ease of use	Easy to use and update
Identification of linkages	Only identified between financial institutions; Not identified between the economy and the financial system.
Likelihood (PD) or impact (LGD)?	LGD
Coverage	
Sectors/Institutions	All financial institutions with market-based high-frequency data on (various) returns (Ex., equity returns, CDS spread changes, returns on market value of assets).
Types of risk	Contribution of one institution to system-wide spillover risk.
Interpretation	
Main output	The fraction of one institution's spillover contribution to all possible spillovers of all other institutions ("contribution" to systemic risk).
Other outputs	The fraction of all possible spillovers received by an institution from others ("vulnerability" to systemic risk).
Thresholds	Yes (e.g., 0.83 for all US institutions and 0.74 for Euro Area institutions signaling 2007-2009 crisis phase)
Time horizon	Good for predicting near-term materialization of financial system-wide stress.
Data requirements	High frequency market-based financial time series; flexible series of returns, but limited to institutions with market data.
Reference	Main: Diebold and Yilmaz, 2009; Users: Arsov and others, 2013.

Methodology

Vector Auto regressions (VAR) of the weekly returns of all institutions are used to derive DY. Specifically, the variance decomposition (VD) at a particular lag (say, 10^{th}) is used to derive a matrix of the portion of variance of the shocks to one institution attributable to another institution. Variance decompositions allow us to assess the fraction of the 10-step-ahead error variance in forecasting x_i that is due to shocks to x_j, $\forall\ j \neq i$, for each i. The DY measure of spillover contributions of institution *i* is the percentage of institution *i* in the total VD of all institutions. The measure is based on central moments, rather than extreme (tail-risk) movements.

Example

	FROM --->																	
Banks TO:	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	Contribution from others
1	60.9	2.4	2.8	0.3	2.1	1.8	6.2	2.7	1.9	1.4	4.7	0.6	4.8	2.4	0.5	2.5	2.0	39.1
2	13.6	50.6	3.4	2.2	2.3	1.2	3.2	0.8	6.1	1.0	4.3	1.0	4.8	1.5	1.0	1.5	1.7	49.4
3	15.8	2.0	58.2	0.2	0.9	2.0	3.7	3.6	2.8	1.3	2.8	1.3	2.3	0.8	0.4	0.8	1.2	41.8
4	5.3	0.8	1.1	81.6	0.4	1.4	2.5	0.6	1.1	1.0	0.2	0.2	0.9	0.9	0.4	0.6	1.1	18.4
5	31.8	1.2	2.2	0.6	33.8	0.9	0.9	1.3	4.4	1.5	3.9	1.7	6.3	2.0	1.8	1.1	4.5	66.2
6	12.1	0.7	2.5	1.0	6.4	45.3	6.4	1.1	1.6	4.1	1.2	3.0	5.2	2.1	1.4	2.9	3.0	54.7
7	31.0	0.8	6.6	0.8	5.5	3.5	29.9	1.1	0.6	2.1	5.5	1.1	3.8	3.6	0.8	1.4	1.8	70.1
8	5.0	2.3	2.6	0.5	1.2	2.0	6.0	69.2	3.7	1.3	2.9	0.4	0.5	0.3	0.3	0.3	1.4	30.8
9	2.4	7.9	5.8	2.5	7.6	0.8	2.3	2.7	58.6	0.9	0.7	0.8	0.2	0.3	1.5	4.1	0.9	41.4
10	8.5	6.0	0.4	1.6	3.7	15.6	6.4	2.0	6.2	26.6	3.5	2.5	6.7	2.6	4.4	2.8	0.6	73.4
11	22.9	2.2	3.0	0.8	1.0	3.4	10.1	2.6	1.8	5.5	33.3	1.0	3.9	2.8	1.0	2.5	2.2	66.7
12	13.8	3.1	3.6	0.2	1.2	3.5	6.4	3.1	5.9	2.1	4.2	40.5	5.0	0.5	0.9	1.8	4.3	59.5
13	21.6	3.4	8.8	0.1	2.6	0.4	3.7	2.5	2.3	0.9	9.7	1.4	36.6	1.2	0.5	0.4	3.9	63.4
14	18.2	1.6	8.1	1.1	2.4	0.8	21.1	2.3	2.6	2.6	9.3	1.9	8.4	17.7	0.1	0.8	0.8	82.3
15	1.7	2.1	5.5	0.7	4.0	3.9	5.8	2.9	31.4	1.9	1.3	1.8	1.1	0.4	29.9	2.2	3.3	70.1
16	2.9	2.4	1.9	0.5	2.3	1.0	2.3	15.0	19.5	1.2	0.2	0.8	0.4	0.2	2.7	44.6	2.0	55.4
17	33.8	2.4	4.9	0.1	2.5	1.8	14.6	2.0	2.8	1.4	5.5	2.1	5.1	2.9	0.6	1.9	15.3	84.7
Contribution to others	240	41	63	13	46	44	102	46	95	30	60	22	60	24	18	28	35	967.3
Contribution including own	301	92	121	95	80	89	132	116	153	57	93	62	96	42	48	72	50	1700
Spillover Index (%)	25	4	7	1	5	5	11	5	10	3	6	2	6	3	2	3	4	57

Source: Based on Arsov and others (2013).

The table shows the variance decomposition based on a VAR(2 lags) of weekly equity returns (in excess of S&P500 returns) of the top 17 United States financial institutions based on the crisis sample 2007–2011, in percent. Banks in columns represent the 'triggers' of shocks, and those in rows, the 'recipient' of shocks. The third row from the bottom shows the contribution of bank i in columns to spillovers into others and is the sum of all the rows under 'i'. The last row (spillover index) computes the same thing, but as percentage of all potential spillovers into others (967.3). For instance, bank 1 is the largest contributor of spillovers, with 25 percent of all spillovers into others, 11 percent by bank 7. From this matrix, bank 1 has the most contribution, and bank 7 has the second-most contribution, to systemic stress. Overall spillover index for the period is 57 (or 0.57 expressed as a fraction).

This matrix could be repeated for windows of data to get a rolling sample, in which case a time-series of the DY index can be derived. A more generalized spillover definition is provided in Diebold and Yilmaz (2012).

IV. DISTRESS SPILLOVERS

This is an indicator of outward-spillovers of institutions or markets during extreme times—the potential contribution of one institution to systemic risk during crisis. The indicator uses market data on returns (based on either CDS spreads or equity prices) to estimate extreme contributions and is easy to use/update. It had reasonable predictions for the interconnectedness among 25 largest banking groups in the world (with pre-crisis data) that proved to be true during the 2007–2009 crisis. It does not identify the exact spillover channels, only those between institutions.

Tool Snapshot

Attributes	Description
Summary properties	
"Systemic reach"	Core financial institutions (listed)
Forward-looking Properties	Good out-of-sample prediction about the interconnectedness among 25 largest banking institutions during extreme times
Ease of use	Easy to use and update
Identification of linkages	Identified among the sample institutions; exact channels not identified
Likelihood (PD) or impact (LGD)?	LGD
Coverage	
Sectors/Institutions	All financial institutions with market-based high-frequency data on (various) returns (Ex., CDS, equity prices, distance-to-default)
Types of risk	Interconnectedness; and contribution of each institution to systemic spillover-risk
Interpretation	
Main output	The fraction of one institution's spillover contribution to all possible spillovers of all other institutions; distress-dependence among institutions.
Other outputs	The fraction of all possible spillovers received by an institution from others ("vulnerability" to systemic risk).
Thresholds	Not available
Time horizon	Good for assessing spillover risk and potential contribution of each institution to systemic risk during stress.
Data requirements	High frequency market-based financial time series; flexible series of returns, but limited to institutions with market data.
Reference	Main: Gropp, Lo Duca and Vesala, 2009; Users: Chan-Lau and others, 2012.

Methodology

It first identifies all extreme events in the data—usually comprising weekly or daily returns on equities, CDS spreads, or market value of assets—by looking at the 1st or the 5th percentile of the joint distribution of returns. All returns lying in the left-tail, that is, the ones below the thresholds, are called 'exceedances'. Then distress-dependence is estimated by using a logit model to account for the fatness of the tails of the distribution of exceedances. In particular, the probability of an exceedance is estimated conditional on exceedances in other financial institutions or centers, after controlling for common shocks such as extreme conditions in the world equity markets, the country's stock markets and real sector indicators. The distress-dependence matrices are largely static—the sample periods are fairly long. The analyses could also be extended to make it more time-varying by repeating the exercise over a rolling window, albeit one that is sufficiently long to provide an adequate number of observations of extreme movements.

Example

Trigger	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17		SC
1			1		1						1				1		1	5	6.2
2							1			1		1	1					4	4.9
3	1										1	1	1		1			5	6.2
4				1		1		1	1	1		1				1		6	7.4
5	1						1		1				1					4	4.9
6				1				1	1	1								4	4.9
7		1			1			1	1							1		5	6.2
8				1		1	1		1	1								5	6.2
9						1	1	1		1					1	1		6	7.4
10		1		1		1		1	1									5	6.2
11	1		1											1			1	4	4.9
12		1		1														2	2.5
13		1	1												1	1	1	5	6.2
14								1			1					1		3	3.7
15	1		1						1				1			1	1	6	7.4
16				1			1		1				1	1	1		1	7	8.6
17	1										1		1		1	1		5	6.2
c	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1		
VIXC			1			1						1							
MSCIWLDC					1		1	1	1	1	1	1		1		1			
sum	5	4	4	5	2	4	5	6	8	5	4	3	6	2	6	7	5	**81**	

Source: IMF Staff estimates.

The table shows the distress dependence between 17 US financial institutions—with 1 indicating the presence (or not) of contagion (to others) potential before the 2007-2009 crisis, at the 5 percent level of significance. The matrix is filled in from logit regressions of the probability of one institution being in distress, conditional on another institution being in distress, controlling for overall market indicators. The rows are the trigger institutions followed by a constant, change in the VIX and MSCI World index. "SC" denotes spillover coefficient. For example, if institution 4 is the trigger, then it contributes to 7.4 percent of all possible outward spillovers. Overall, total spillover coefficient is 81/(16*17) = 0.30. This can be compared to another period. The table can also be replicated for the marginal effects derived from the regressions, in which case the intensity of spillovers can be derived.

V. Market-Based Probability of Default

A market-based default measure provides a forward-looking indicator of default risk by estimating the likelihood that an institution's future value of assets will fall below its distress point. It combines market data on traded equity (market cap, equity return, and equity volatility) or traded CDS, with balance sheet data on outstanding debt to construct default measures at different horizons.

Tool Snapshot

Attributes	Description
Summary properties	
"Systemic reach"	Listed financial institutions or with active CDS markets
Forward-looking Properties	Provides one through five years forecast estimates
Ease of use	Easy to use and update
Identification of linkages	N/A
Likelihood (PD) or impact (LGD)	PD and LGD
Coverage	
Sectors/Institutions	All financial institution with balance sheet data and equity market data
Types of risk	Credit risk
Interpretation	
Main output	PD (risk neutral measure), EDF (physical measure)
Other outputs	Distance to default, Loss given default, Implied Haircut, and Equity-based fair value CDS
Thresholds	No
Time horizon	Short-term through medium-term predictive power
Data requirements	Traded equity data (equity value, equity return, equity volatility) or CDS and balance sheet data (debt face value and maturity structure)
Reference	Kealhofer, 2003

Methodology

This methodology applies the insight by Black, Scholes, and Merton that views a firm's debt as an option on the asset value of the firm. An option valuation approach can thus be applied to assess the default risk of a firm with traded equity (or credit spreads). The distance to default (dtd) at time t of a firm with inferred value of assets V_t, asset volatility σ_t^2 , face debt value D, risk-free rate of return r, and time to maturity (T-t) is given by:

$$dtd_t^T = \frac{\ln\left(\frac{V_t}{D}\right) + \left(r - \frac{\sigma_t^2}{2}\right)(T-t)}{\sigma_t\sqrt{(T-t)}}$$

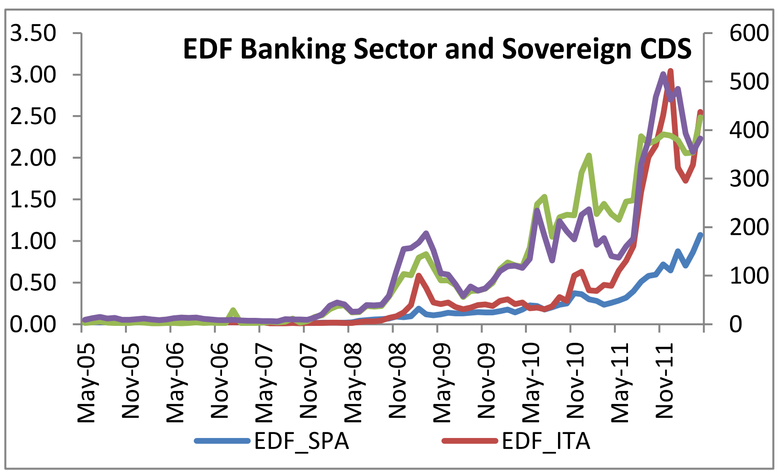
Under standard distributional assumptions in the stochastic process of the firm's value, the risk-neutral PD is characterized by:

$$PD_t^T = 1 - N\left(dtd_t^T\right)$$

Moody's KMV has applied this valuation framework to compute a physical measure of default risk. Using a long time series with over 30,000 public companies worldwide, it has identified the proportion of firms with a certain distance to default that actually defaulted within a specific forecasting window. This is the expected default frequency (EDF). For nontraded firms with active CDS markets (including sovereigns) KMV offers estimates of the PD, LGD, and risk premium embedded in credit spreads and derives a CDS-implied EDF credit measure.

Example

The Moody's KMV methodology has been applied to estimate the individual EDF of the largest five banks in Spain and Italy. The figure below shows the asset value-weighted EDF for the Spanish and Italian banking sector. The waves in bank credit distress unleashed in February 2009 and April 2011 comove positively with the spikes in government credit risk reflected in the sovereign CDS market.



Source: Authors' calculation.

VI. Debt Sustainability Analysis (DSA)

DSA examines the effect on the public debt-to-GDP dynamics of several shocks such as real interest rate shock, GDP shock, and a realization of contingent liabilities including financial sector bailout, specified as an exogenous increase in the debt ratio of 10 percent of GDP. It is easy to use and update, but is not linked to any estimate of shocks.

Tool Snapshot

Attributes	Description
Summary properties	
"Systemic reach"	Public sector
Forward-looking Properties	Not forward-looking in the sense that assumed shocks are not forward-looking
Ease of use	Easy to use and update
Identification of linkages	Impact of real economy, market, and financial system on sovereign risk
Likelihood (PD) or impact (LGD)?	LGD (the effect on the financial sector if debt/GDP were to increase by "x" following a common set of shocks)
Coverage	
Sectors/Institutions	Public sector
Types of risk	Sovereign risk
Interpretation	
Main output	Public debt-to-GDP ratio
Other outputs	N.A.
Thresholds	No
Time horizon	Typically five years
Data requirements	GDP, inflation, public debt, public revenue and expenditure, interest rate on public debt, and public debt composition
Reference	IMF, 2002 and 2003

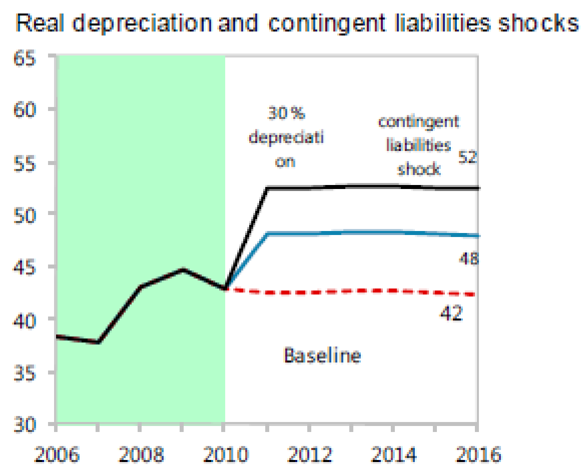
Methodology

The sensitivity test on sovereign risk by DSA consists of three steps.

The first step sets a baseline scenario on key economic variables such as GDP growth rate and inflation rate as well as interest rate on public debt. The second step projects public debt to GDP ratio using estimated flows of revenue and expenditure under the baseline scenario. The final step examines the dynamics of public debt to GDP ratio under several shock scenarios including rise in real interest rate, decline in GDP growth rate and a realization of contingent liabilities by 10 percent of GDP.The specification of shock scenario is not based on any estimates. So, for example, the contingent liability test should be refined by several approaches such as stress test that provides an estimate of the fiscal cost of bank recapitalization in case of the materialization of various risks, cross country evidence on past banking system crises that presents crude estimates of the possible contingent liabilities, and other estimates of contingent liabilities by sophisticated method such as systemic CCA.

Example

The chart shows the dynamics of public debt-to-GDP ratio if one time 10 percent of GDP shock to contingent liabilities occurs in 2010. DSA related documents of individual countries are available on the DSA website (http://www.imf.org/external/pubs/ft/dsa/index.htm).



VII. Indicators of Fiscal Stress

This methodology provides a framework to assess fiscal vulnerability and evaluate the likelihood of a full-blown fiscal crisis based on the construction of a coincident indicator of rollover pressure and a forward-looking index of extreme fiscal stress. It can be used as an effective fiscal monitoring tool of sovereign risk based on fiscal fundamentals.

Tool Snapshot

Attributes	Description
Summary properties	
"Systemic reach"	Public sector
Forward-looking Properties	The fiscal stress index provides an early warning indicator of fiscal tail events although its statistical power is relatively weak
Ease of use	Easy to use and update
Identification of linkages	Not identified. Thresholds are estimated using a univariate nonparametric model
Likelihood (PD) or impact (LGD)?	PD
Coverage	
Sectors/Institutions	Public sector
Types of risk	Sovereign risk
Interpretation	
Main output	A country specific fiscal vulnerability index and a fiscal stress index.
Other outputs	Fiscal vulnerability measures can be aggregated for advanced and emerging economies.
Thresholds	Yes
Time horizon	Coincident and medium term indicators.
Data requirements	Low frequency macroeconomic and financial data.
Reference	Baldacci, McHugh and Petrova, 2011

Methodology

This approach builds on the construction of two signaling tools. First, a fiscal vulnerability index measuring the deviation of a set of fiscal indicators—including underlying fundamentals, long-term fiscal needs, and rollover risk—from a historical peer-group average. Each indicator x_t^i is standardized to z_t^i and mapped into a cumulative normal distribution ranging from 0 to 10.

$$z_t^i = \frac{x_t^i - \mu}{\sigma_i}$$

Second, a fiscal stress index is computed on the basis of a number of fiscal indicators exceeding endogenous thresholds—that minimize noise to signal ratios of future fiscal crises—weighted by their relative signaling power.

Example of Tool Use

The table below shows the fiscal vulnerability index, the fiscal stress index, and a combined risk score computed as a simple average of the two indices, for three clusters of fiscal variables including basic fiscal variables, long-term fiscal needs, and asset and liability indicators. The results are calculated in the Fall of 2010 for a sample of G-20 countries and Greece, Ireland, Portugal and Spain (GIPS) and are displayed separately for advanced and emerging economies. Index values close to 10 indicate high levels of vulnerability while values close to 5 signal a normal degree of vulnerability.

	Basic Fiscal Variables	Long-term Fiscal Trends	Asset and Liability Management	Overall Score
Fiscal Vulnerability				
G20 Advanced plus GIPS	7.7	6.0	6.0	6.5
G20 Emerging Economies	6.9	5.0	6.0	6.0
Fiscal Stress				
G20 Advanced plus GIPS	7.2	7.3	8.3	7.4
G20 Emerging Economies	7.1	4.8	3.9	5.0
Aggregate Score				
G20 Advanced plus GIPS	7.5	6.6	7.2	7.0
G20 Emerging Economies	7.0	4.9	5.0	5.5

Source: Baldacci and others (2011).

VIII. Sovereign Funding Shock Scenarios

The framework for sovereign Funding Shock Scenarios (FSS) evaluates the vulnerability of sovereigns to sudden stops—situations when foreign investors stop buying or start selling off their holdings of government bonds. It assesses the potential impact of foreign investor outflows on the balance sheet of the domestic banking system and how it may affect sovereign-bank linkages. It is easy to update and can be used along with standard debt sustainability analyses (DSA).

Attributes	Description
Summary properties	
"Systemic reach"	Public sector
Forward-looking Properties	The FSS provides an early warning indicator of the potential impact of sudden shifts in behavior of sovereign bonds investors
Ease of use	Easy to use and update
Identification of linkages	Assessment of sovereign funding needs and impact from sudden investor outflows on sovereign-bank linkages
Likelihood (PD) or impact (LGD)?	LGD
Coverage	
Sectors/Institutions	Public sector
Types of risk	Sovereign risk
Interpretation	
Main output	Banking sector exposure to own government debt (in percent of bank assets)
Other outputs	Sovereign funding needs under different scenarios of foreign investor outflows
Thresholds	N/A
Time horizon	Forward-looking (one year ahead)
Data requirements	Sovereign gross financing needs, sovereign debt investor base, banking sector assets
Reference	Arslanalp and Tsuda, 2012

Methodology

The FSS aims to assess the sovereign's ability to manage a hypothetical loss of international market access—a funding shock triggered by pull-out of foreign investors over a year—through greater reliance on domestic investors.

The analysis relies on three parameters regarding investment decisions of foreign private investors over a one year horizon, namely: (i) their contribution to funding of the overall fiscal deficit (α); (ii) their rollover of *short-term* government debt (by residual maturity) (β); and (iii) their sale of *long-term* government debt (by residual maturity) (γ). The holdings of foreign official investors are assumed to stay constant over the next year.

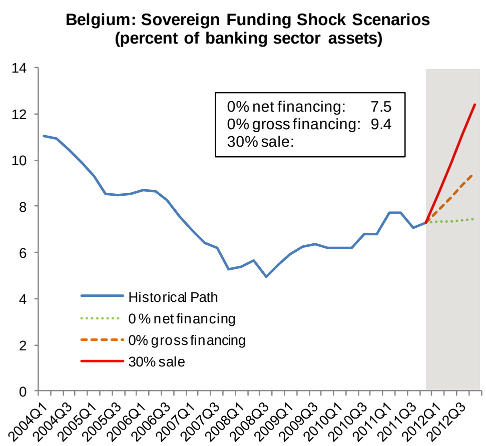
Based on this framework, three scenarios are considered: (i), foreign private investors provide no new *net* financing (α=0, β=100, γ=0); (ii), foreign private investors provide no new *gross* financing (α=β=γ=0), and (iii) foreign private investors provide no new *gross* financing and sell off 30 percent of their remaining holdings (α=β=0, γ=30). This is the most severe scenario and is intended to replicate the average experience of Greece, Ireland, and Portugal during the worst part of their sovereign debt crisis.

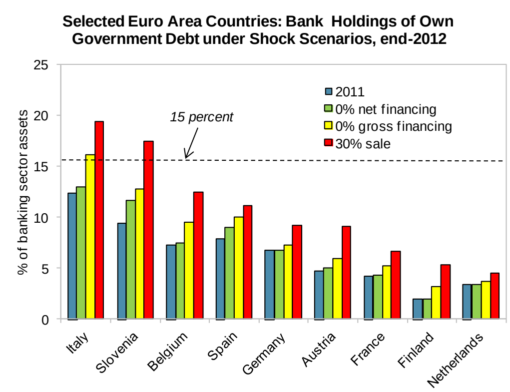
A large increase in banking sector asset under the shock scenarios implies that: (i) sovereign-banking linkages may grow substantially with adverse effects for domestic financial stability and growth prospects due to crowding out; and/or (ii) domestic bank may face difficulty absorbing the sovereign funding needs and, as a result, sovereign bond yields may rise.

Example

The results of the FSS can be analyzed through both time-series and cross-sectional presentations:

- ***Time-series.*** The first chart below shows the level of sovereign debt held by domestic banks before and after the shock scenarios for Belgium.
- ***Cross-section.*** The second chart shows how Belgium compares to other advanced economies in terms of their vulnerability to the same shocks.





IX. ASSET PRICE MODELS

Asset price models detect signs of asset price misalignment by identifying fundamental demand and supply disequilibria using macroeconomic, financial, and balance sheet data. They are used to assess the likelihood of market price corrections, and their potential impact on the real economy.

Tool Snapshot

Attributes	Description
Summary properties	
"Systemic reach"	Systemic risk at the country level focusing on the financial sector, the corporate sector, the household sector, and the broader economy.
Forward-looking Properties	Yes, through measure of likelihood of asset price correction
Ease of use	Easy to construct based on data availability, currently covering between 15 and 22 advanced economies, and up to 19 emerging economies.
Identification of linkages	Assessment of likelihood of price correction, and impact from expected decline on the real economy.
Likelihood (PD) or impact (LGD)	PD and LGD (in the form of GDP-effect)
Coverage	
Sectors/Institutions	Key asset markets, and country risk (impact on GDP growth from price corrections—households, corporates, and financial institutions are covered)
Types of risk	Market risk from shocks to residential and commercial real estate prices, spikes in corporate bond spreads, and equity price declines
Interpretation	
Main output	A country-level index of vulnerability to downward asset price corrections
Other outputs	Estimated impact on GDP from a house price correction. Co-movement between corporate bond spreads and macrofinancial determinants. Degree of overvaluation relative to fundamentals, past valuation ratios, and cross-country distributions in the form of a heat map or a wheel
Thresholds	Overvaluation is deemed significant when it exceeds 10 percent of fundamentally-implied prices, one standard deviation above its historical mean, or lies in the top third quartile of the cross-country benchmark distribution
Time horizon	Contemporaneous measure of vulnerability
Data requirements	Quarterly/monthly macroeconomic, market-based, and balance sheet data from OECD, WEO, IFS, Haver Analytics, Knight Frank LLP, Global Property Guide, Consensus Forecast, and Bloomberg
Reference	IMF-FSB, 2010

Methodology

The *real estate vulnerability index* is constructed by combining four indicators that capture the extent of price misalignment, the stress in household balance sheets, the exposure to market risk from mortgage contract provisions, and the impact of an asset price correction on real economic activity. The *corporate vulnerability index* is a normalized weighted sum of leverage, liquidity, and profitability indicators capturing the probability of corporate distress, multiplied by its potential macroeconomic impact proxied by the market capitalization of listed companies. The degree of *equity price misalignment* is assessed using a historical time series on price-to-book and price-to-expected earnings ratios, the dividend-based Gordon valuation model and the following arbitrage pricing model:

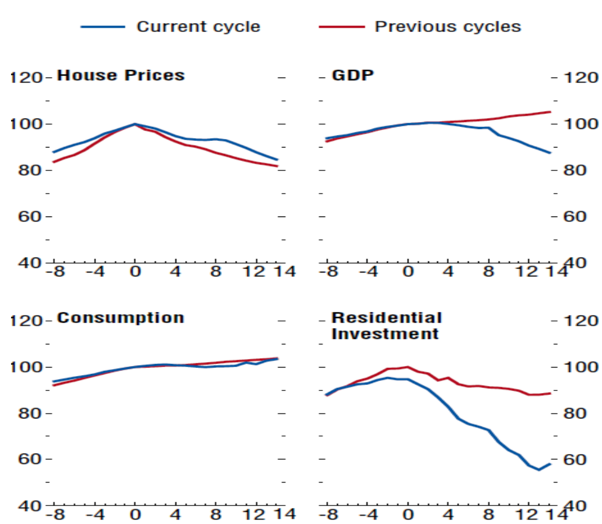
$$R_{i,t} = \alpha_i + \sum_j \beta_{i,j} F_{j,t} + \varepsilon_{i,t}$$

where $R_{i,t}$ denotes monthly excess return on country i's stock market index over the risk-free rate, and $F_{j,t}$ capture various measures of risk premia.

The *spillovers* from an asset price correction on GDP are measured using a VAR specification that includes a set of macroeconomic variables, a monetary policy reaction function, and real house prices. Finally, the *corporate bond valuation* model estimates the impact on corporate spreads from changes in operating/investing/financing cash flows of bond issuers and holders driven, which are driven by the business cycle, market price fluctuations and financing constraints.

Example

An econometric model has been used to estimate the price correction of residential house prices in advanced economies if the gap between 2010 house prices and their fundamental values—based on changes in per capita disposable income, working-age population, construction costs, credit and equity prices, and interest rates—were to close over the next five years. Real house prices would fall at an annual rate of between 0.5 percent and 1.5 percent on average between 2010 and 2015 and residential investment would remain depressed for several years.



Source: IMF, 2010.

X. Balance Sheet Approach

This analytical framework examines the balance sheet of an economy's major sectors, identifies maturity, currency, and capital structure mismatches, and drills down intersectoral linkages across domestic sectors and to the rest of the world. This is a useful tool for analyzing the resilience of the main economic sectors to specific financial shocks and the transmission of shocks across sectors.

Tool Snapshot

Attributes	Description
Summary properties	
"Systemic reach"	Linkages across all major sectors of the economy and to the rest of the world
Forward-looking Properties	N/A
Ease of use	Easy to use and update
Identification of linkages	Cross-sectoral claims and liabilities are identified
Coverage	
Sectors/Institutions	Public sector, financial sector, corporate sector, household sector, and nonresident sector
Types of risk	Counterparty risk, exchange rate risk, liquidity risk, and solvency risk
Interpretation	
Main output	A balance-sheet matrix displaying each sector's claims on other sectors and liabilities to other sectors
Other outputs	Sensitivity tests to specific financial shocks
Thresholds	N/A
Time horizon	Provides a coincident measure of interconnectedness. Suitable for conducting a stress testing analysis
Data requirements	Low-frequency data from national sources. Stock variables for the nonfinancial private sector are typically derived from the balance-sheet positions of other sectors
Reference	Allen, Rosenberg, Keller and others, 2002

Methodology

The BSA views the economy as a system of sectoral balance sheets displaying book valued stocks of assets and liabilities at a specific point in time. In a first step, four main sectors are identified, namely the government sector (including the central bank), the financial sector (mainly the banking system), the nonfinancial sector (corporations and households), and the external sector (nonresidents). For each sector, a breakdown of claims and liabilities by currency and maturity allows to examine four general types of risks, i.e. maturity risk, currency risk, credit risk, and solvency risk. Sectoral balance sheets provide valuable information on potential sources of risk that may be masked by the netting off of exposures under consolidated country balance sheet data.

Example of Tool Use

The BSA framework has been applied to Croatia to examine how sectoral interlinkages have shifted with the surge in external debt to near 86 percent of GDP in 2006. A comparison of the banking sector's balance sheet position at end-2000 (Table 1) and at end-2005 (Table 2) reveals a significant increase in net exposures to the central bank and the government sector following a hike in reserve requirements and increased public bond issuance. More significantly, it reflects a sharp increase in external borrowing with a near threefold rise of foreign liabilities. Overall, the nonresident sector increased its exposure to Croatia by 100 billion kuna or 37.4 percent of GDP over the period.

Table 1. Croatia: Net Intersectoral Asset and Liability Positions (in millions of Kuna) -December 2000

Debtor	**Central Bank**		**Central Government**		**Banking sector**		**Corporations**		**Households**		**Rest of the world**	
Creditor	Claims	Liabilities	Claims	Liabilities	Claims	Liabilities	Claims	Liabilities	Claims	Liabilities	Claims	Liabilities
Central government	0	1157			19055	6730	...	...	...	...	40093	582
Banking sector	330	14434	6730	19055			14617	33447	49464	23298	17810	19710
Corporations	8	150	...	...	33447	14617			...	...	33776	11232
Households	68	0	...	...	23298	49464	...	...			...	...
Rest of the world	28832	1631	582	40093	19710	17810	11232	33776	...	...		

Table 2. Croatia: Net Intersectoral Asset and Liability Positions (in millions of Kuna) -December 2005

Debtor	**Central Bank**		**Central Government**		**Banking sector**		**Corporations**		**Households**		**Rest of the world**	
Creditor	Claims	Liabilities	Claims	Liabilities	Claims	Liabilities	Claims	Liabilities	Claims	Liabilities	Claims	Liabilities
Central government	1	345			29191	9336	...	...	...	...	51983	465
Banking sector	4222	39566	9336	29191			34598	61175	100381	78971	67800	35969
Corporations	13	0	...	...	61175	34598			...	...	73256	11134
Households	22	0	...	...	78971	100381	...	...			...	...
Rest of the world	54908	19	465	51983	35969	67800	11134	73256	...	...		

Source: IMF (2007).

XI. SYSTEMIC CCA

The systemic Contingent Claims Approach (CCA) extends CCA to quantify the system-wide financial risk and government contingent liabilities by combining individual risk-adjusted balance sheets of financial institutions and the dependence between them. It provides forward-looking estimates.

Tool Snapshot

Attributes	Description
Summary properties	
"Systemic reach"	Aggregation of core financial institutions (listed)
Forward-looking Properties	Coincident indicator of interconnectedness
Ease of use	Not easy to use and update
Identification of linkages	Linkage between financial system and sovereign risk
Likelihood (PD) or impact (LGD)?	LGD and conditional PD
Coverage	
Sectors/Institutions	All financial institution with balance sheet data and high frequency market data (equity options and CDS)
Types of risk	Contribution of each institution to system-wide distress, and spillover risk in general
Interpretation	
Main output	Total expected loss in the financial system and government contingent liabilities
Other outputs	Unexpected loss and extreme risk in the financial system
Thresholds	No
Time horizon	Coincident indicator of interconnectedness
Data requirements	Daily market capitalization of each institution, default barrier estimated for each institutions based on quarterly financial accounts, risk-free interest rate and one-year CDS spreads
Reference	Gray and Jobst, 2011

Methodology

The systemic CCA can be decomposed into two estimation steps. The first step uses CCA to estimate the market-implied potential losses for each sample financial institution (see CCA). The second step uses Extreme Value Theory to model the joint market-implied losses of multiple institutions as a portfolio of individual losses with time-varying and nonlinear dependence among institutions and estimates system-wide losses.

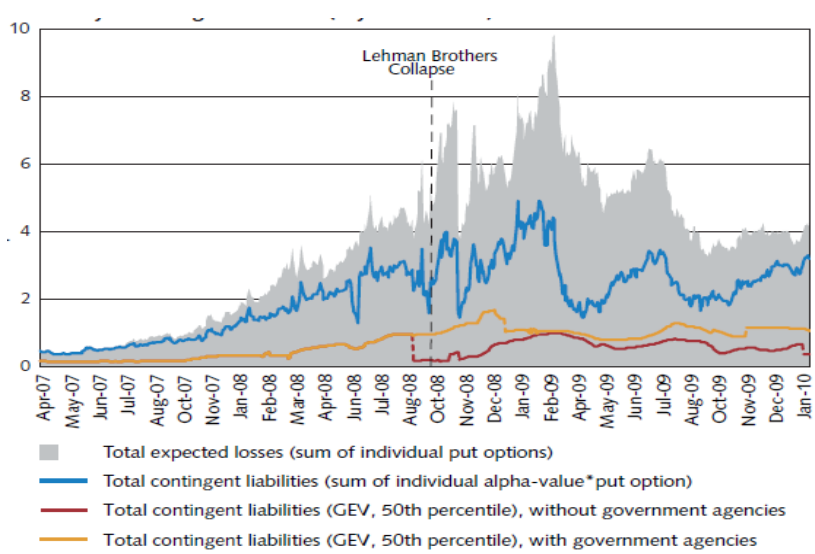
In the second step, firstly, a nonparametric dependence function of individual potential losses is defined. Then, this dependence measure is combined with the marginal distributions of these individual losses, which are assumed to be generalized extreme value. These marginal distributions are estimated via the Linear Ratio of Spacings (LRS) method. Secondly, the multivariate dependence structure of joint tail risk of potential losses is derived nonparametrically. Finally, after estimation of the marginal distributions and the dependence structure, the following point estimates of joint potential losses at quantile $q = 1 - a$ at any point time t is derived.

$$\hat{\chi}_{a,p,t} = G^{-1}_{\hat{\xi},\hat{\mu},\hat{\sigma}}(a) = \hat{\mu}_j + \hat{\sigma}_j/\hat{\xi}_j\left(\left(-\frac{\ln(a)}{A(\omega)}\right)^{-\hat{\xi}_j} - 1\right),$$

with location parameter μ, shape parameter ξ, and multivariate dependence structure of joint tail risk of potential losses $A(\omega)$.

Example

Country/Financial institutions: 36 financial institutions covering bank holding companies, other banks, major broker dealers, GSEs, and insurance groups. The chart shows total expected losses and government contingent liabilities. Both are highest between the periods just after Lehman's collapse in September 2008 and the end of July 2009.



Source: Gray and Jobst (2011).

XII. Cross-Border Interconnectedness

The network model uses annual cross-border banking sector exposures to construct a measure of global interconnectedness. It also estimates the impact of interconnectedness on the likelihood of a banking crisis within a one-year forecast window using an econometric specification.

Tool Snapshot

Attributes	Description
Summary properties	
"Systemic reach"	Global banking system through cross-border banking system exposures for which BIS locational statistics on cross-border exposures are available
Forward-looking Properties	One year forecasting window
Ease of use	Easy to use and update.
Identification of linkages	Downstream interconnectedness (cross-border asset exposure), and upstream interconnectedness (cross-border liability exposure).
Likelihood (PD) or impact (LGD)	PD
Coverage	
Sectors/Institutions	Banking sector
Types of risk	Risk of a banking crisis from contagious defaults
Interpretation	
Main output	Probability of a banking system's default conditional on its cross-border interconnectedness
Other outputs	Combination of interconnectedness thresholds to identify "high" and "low" crisis probability areas, using a nonparametric approach
Thresholds	An increase in upstream interconnectedness below 0.37 (95 percent of the interconnectedness observations in the sample) calibrated at average macroeconomic variables reduces the probability of a banking crisis. When upstream interconnectedness is above 0.37 (the remaining 5 percent), the relationship between interconnectedness and crisis probability is more complex: it is upward sloping at first, only to become downward sloping again
Time horizon	The interconnectedness measure has forecasting ability one year ahead
Data requirements	Low frequency data from BIS quarterly locational banking statistics, macroeconomic and bank balance sheet data, and banking crisis dummy from Laeven and Valencia (2008) database
Reference	Čihák, Muñoz, and Scuzzarella, 2011

Methodology

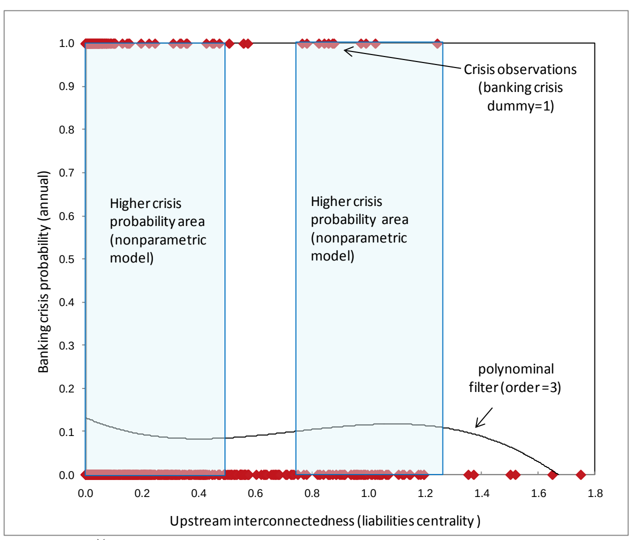
The network model examines the impact of a banking system's interconnectedness (node centrality) on the probability of a banking crisis using an econometric specification that controls for a set of macroeconomic and institutional variables. The estimated log-likelihood function is:

$$\ln L = \sum_t \sum_i \{P(i,t)\ln[F(\beta' X(i,t))] + (1 - P(i,t))\ln[1 - F(\beta' X(i,t))]\}$$

where $P(i,t)$ is the banking crisis dummy variable proposed by Laeven and Valencia (2008), and $X(i,t)$ the vector of explanatory variables. Based on a banking system's "alter-based centrality" notion that shows its relative importance in cross-border exposures in the global banking network, two measures of interconnectedness are created: downstream interconnectedness (asset centrality) and upstream interconnectedness (liability centrality). The level and slope effects of interconnectedness on the likelihood of a banking crisis are estimated using a multivariate probit model approach and a nonparametric algorithm.

Example

Using a sample of 189 banking systems over 1977-2009, an M-shaped curve showing a non-linear relationship between the likelihood of a banking crisis and its interconnectedness to the global banking network is obtained. In a country whose banking sector has relatively few linkages to other banking sectors, increased cross-border linkages tend to improve that system's stability, controlling for other factors. But at some point—the 95th percentile of the distribution of countries in terms of interconnectedness—increases in cross-border links begin to have detrimental effects on domestic banking sector stability. At a yet higher point, when a country's network of interlinkages becomes almost complete, the probability of a crisis goes down again. This effect is stronger for funding-recipient banking systems than for funding-provider banking systems.



Source: Čihák, Muñoz, and Scuzzarella (2011).

XIII. Cross-border Network Contagion

The network analysis model measures interconnectedness among banking systems and traces a spillover path from one institution's insolvency and/or funding difficulties to others. It uses consolidated cross-border banking statistics from BIS. It uses data on actual exposures across banking systems and gives an estimate of both "loss given default" and the spillover-direction. In essence, the methodology could be replicated with inter-institution exposures to measure domestic interconnectedness, if such data is available.

Tool Snapshot

Attributes	Description
Summary properties	
"Systemic reach"	Global banking system through cross-border banking system exposures for which BIS locational statistics on cross-border exposures are available.
Forward-looking Properties	Not known
Ease of use	Easy to use
Identification of linkages	Identified among the sample countries
Likelihood (PD) or impact (LGD)?	LGD
Coverage	
Sectors/Institutions	Aggregate of banking system-level data (from BIS)
Types of risk	Interconnectedness; and contribution of each institution to systemic spillover-risk
Interpretation	
Main output	The impact on regulatory capital of one banking system, from failure or funding difficulties of another system.
Other outputs	The fraction of one banking system's spillover contribution to all possible spillovers of all other institutions ("contribution" to systemic risk); contagion path of bank-failures; The fraction of all possible spillovers received by an institution from others ("vulnerability" to systemic risk)
Thresholds	Not available
Time horizon	Good for assessing spillover risk and potential contribution of each institution to systemic risk
Data requirements	Cross-border exposure data from BIS and regulatory capital from http://fsi.imf.org/
Reference	Espinosa-Vega and Sole, 2010; Users: IMF, 2011a

Methodology

The data consists of a matrix of bilateral banking system exposures from the BIS (Table 9B). The matrix is complemented by data on regulatory capital of the countries' banking sectors. Using the methodology in Espinosa-Vega and Sole (2010), we can then trace the network spillovers resulting from hypothetical credit and funding events to specific banking systems. In particular, two sets of simulations are done. First, is a simulation of a banking system becoming insolvent and being unable to repay interbank loans in others. Second, is a simulation of a banking system becoming insolvent, not repaying loans in others and unable to rollover funding from others.

Example

This method was applied in the context of the Spillover Report for Japan (IMF 2011a). Besides Japan, the countries included in the analysis were Australia, Austria, Belgium, Canada, France, Germany, Ireland, Italy, Japan, Netherlands, Portugal, Spain, Sweden, Switzerland, United Kingdom, United States, China, Taiwan, India, Indonesia, Malaysia, Philippines, South Korea, Thailand, and Vietnam. The table shows the impact on Japan (on others) if another banking system (Japan) fails. The shocks considered are solvency shock (with loss-given-default as 1) and a combination of a solvency and funding shock (with the borrowing institution not being able to replace 0.35 fraction of its funding from a defaulting institution).

Capital impairment (in percent of pre-shock capital)

	Impact on Japan if trigger country defaults			Impact on others if Japan	
Trigger country	Credit shock 1/	Credit & Funding shock 2/	*Affected countries*	Credit shock 1/	Credit & Funding shock 2/
Australia	-4.4	-4.5	Australia	-2.2	-8.8
France	-6.2	-72.3	France	-10.8	-13.8
Germany	-7.2	-72.3	Germany	-2.6	-7.2
Ireland	-3.1	-72.3	Ireland	-10.5	-11.7
Italy	-0.5	-72.3	Italy	-0.2	-0.5
Portugal	0.0	0.0	Portugal	0.0	-0.3
Spain	-0.6	-0.7	Spain	-0.8	-1.5
UK	-57.6	-72.3	UK	-25.3	-39.7
US	-35.8	Full	US	-9.6	-14.6
China	-1.6	-1.9	China	-1.3	-2.2
Taiwan	-0.2	-0.4	Taiwan	-5.9	-6.8
India	-0.4	-0.5	India	-0.2	-1.3
Indonesia	-0.4	-0.4	Indonesia	-1.6	-5.7
Malaysia	-0.2	-0.2	Malaysia	-1.4	-3.0
Philippines	0.0	-0.1	Philippines	-5.4	-6.0
South Korea	-3.1	-3.2	South Korea	-4.1	-14.7
Thailand	-0.6	-0.6	Thailand	-2.9	-7.2
Vietnam	-0.1	-0.1	Vietnam	-0.9	-2.6

1/ Assumes loss-given-default or lambda is 1. The figures represent the direct and indirect effects of failures.
2/ This results of this shock are highly sensitive to the choice of parameters. The benchmark assumes lambda=1, rho=0.35.

Source: IMF (2011a).

XIV. Systemic Liquidity Risk Indicator

The Systemic Liquidity Risk Indicator (SLRI) is constructed from data on violations of arbitrage relationships in the global financial system. It measures the intensity of liquidity shortages in global markets, working as a high frequency indicator of tail liquidity risks. It is easy to use/update. It should be view as a coincident indicator of systemic liquidity shortages, albeit it has been shown to forecast extreme crisis events in the banking sector.

Tool Snapshot

Attributes	Description
Summary properties	
"Systemic reach"	Global markets.
Forward-looking Properties	Coincident indicator of systemic liquidity shortages. It can forecast, on a high frequency basis, extreme shocks to banks
Ease of use	Easy to use and update
Identification of linkages	Exposures of banks to the SLRI measure the connectivity in terms of liquidity risk
Likelihood (PD) or impact (LGD)?	PD
Coverage	
Sectors/Institutions	Global capital markets. In general, it cannot be used to evaluate liquidity risks in individual markets, unless there is a high degree of segmentation
Types of risk	Contractions in market and funding liquidity at a global level
Interpretation	
Main output	An index variable that moves down when global liquidity dries out
Other outputs	Exposure of individual banks to the SLRI, measured as betas on the mean and volatility of banks' equity returns. It can also be used to calculate a premium to be paid by banks as a compensation for the implicit liquidity support obtained from public authorities
Thresholds	There are no specific thresholds. The index is normalized to have 0 mean and unit standard deviation. Usually, values above 2 indicate important liquidity shortages
Time horizon	Good for predicting very short term tail shocks to financial institutions. No medium or long-term predictive power
Data requirements	High frequency (daily or weekly) data on asset prices
Reference	Severo, 2012; Users: IMF, 2011d

Methodology

The computation of the SLRI requires time series data on various arbitrage or quasi-arbitrage relationships in asset markets. For example, one can use data on violations of covered interest parity for many pairs of currencies, the CDS-Bond basis for corporate and sovereign bonds, the U.S. Treasury's on-the-run off-the-run spread (OOS), etc. Collect this information on a matrix X and use Principal Components Analysis (PCA) to extract orthogonal factors which are ranked according to their ability to explain the variation in the data. The first factor is the SLRI, provided it explains a significant portion of the variability in the data. One can test whether banks or other financial institutions are exposed to the SLRI by running a regression of equity returns R (or CDS spreads) against the SLRI and other control variables Z.

$$R^i(t) = Z(t)\beta^i + \beta_L^i SLRI(t) + e^i(t)\sigma^i(t)$$

$$\sigma^i(t)^2 = \exp\left(Z(t)\omega^i + \omega_L^i SLRI(t)\right) + \gamma^i e^i(t-1)^2$$

Note that the SLRI can affect both the mean and volatility of returns, since liquidity shortage increases the riskiness of financial institutions. $e^i(t)$ is a white noise shock.

Example

Liquidity conditions during the 2008 crisis. Daily data on 36 violations of arbitrage including CIP, CDS-Bond basis, OOS and the Bond-Swap basis, from 2004 until 2010. Similar data on equity returns from 53 global or regionally important banks across the globe. Figure 1 shows the evolution of the SLRI over time. It illustrates the sharp reduction in global liquidity around the Lehman debacle in 2008. Figure 2 shows the average (by location) annualized bank return volatility under normal liquidity conditions (SLRI = 0, light green bar) and under liquidity stress (SLRI = 2 std below its mean, dark green bar). Clearly, global liquidity shortfalls increase substantially the riskiness of banks.

Figure 1

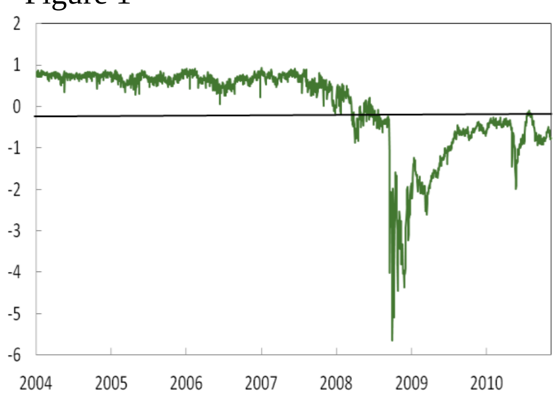
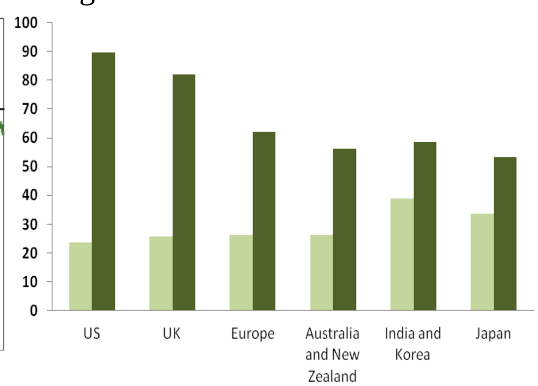


Figure 2



Source: Severo (2012).

XV. Regime-Switching Volatility Model

The Regime-Switching Volatility Model uses high frequency data on asset prices and related financial variables to assess the likelihood that the financial system as whole will enter different states regarding uncertainty and systemic risk.

Tool Snapshot

Attributes	Description
Summary properties	
"Systemic reach"	Can be used to measured uncertainty in global markets as well as in specific market segments (FX for example)
Forward-looking Properties	Reasonable in-sample forecast. Indicated early in 2007 the possibility of a high volatility regime in global financial markets
Ease of use	Easy to update
Identification of linkages	Not identified
Likelihood (PD) or impact (LGD)?	PD
Coverage	
Sectors/Institutions	Global or domestic markets on aggregate, or specific market segments (e.g., FX or interest rate markets)
Types of risk	General degree of uncertainty, risk of systemic events
Interpretation	
Main output	The probability of financial markets being in different regimes, characterized by low, medium of high volatility (can be extended to consider more than 3 states)
Other outputs	Estimates of the time-varying volatility of the financial variables considered
Thresholds	No specific thresholds. Rule of thumb would be to consider a systemic event when the probability of being in a high volatility state surpasses 50%
Time horizon	Good for predicting near-term materialization of financial system-wide stress
Data requirements	High frequency market-based financial time series
Reference	Hamilton and Susmel, 1994; Users: Gonzalez-Hermosillo and Hesse, 2009

Methodology

The basic methodology assumes that a certain variable Y which reflects information about general financial conditions (e.g., the VIX, the Ted spread, the Euro-Dollar Forex Swap, etc) follows a univariate ARCH Markov-Switching model. More specifically, Y is assumed to evolve as:

$$Y_t = \alpha + \phi Y_{t-1} + \epsilon_t$$
$$\epsilon_t = \sqrt{g_t}\tilde{\epsilon}_t$$

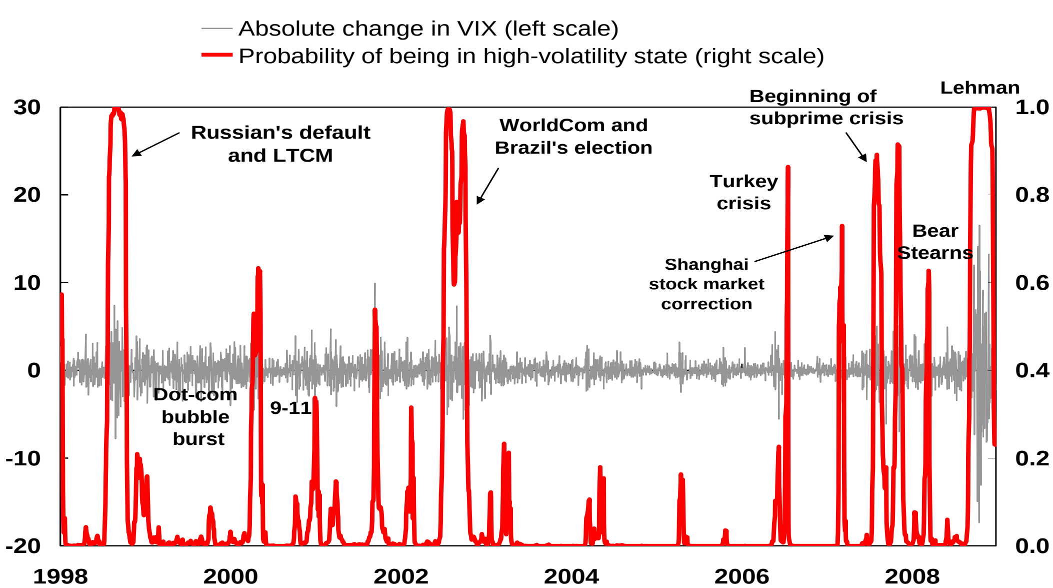
$\tilde{\epsilon}_t$ is the product of a unit-variance, zero-mean normally distributed random variable and a time-varying volatility σ such that:

$$\sigma_t^2 = a + b\tilde{\epsilon}_{t-1}^2$$

The parameter g_t assumes different values in different states of nature. It indicates whether the system is at low or high volatility regime, for example. The model is estimated by maximum likelihood.

Example (VIX and probability of a high volatility regime over time)

This example uses daily data on the VIX between 1998 and 2008 to estimate the probability that financial markets would experience a high volatility regime (when risks become systemic). It shows that, during the Lehman episode, the volatility of VIX reached historic highs. Moreover, the figure suggests that markets signaled at the very beginning of the subprime crisis an elevated probability of a regime characterized by high volatility, where systemic events become more likely.



Source: Hermosillo and Hesse, 2009.

XVI. Financial Soundness Indicators (FSIs)

FSIs are indicators of the current soundness of the financial system in a country, and of its corporate and household counterparties. FSIs include both aggregated individual financial institution data and indicators that are representative of the markets in which the financial institutions operate. They are easy to use and update, but do not measure precisely the likelihood of, or resilience against future shocks.

Tool Snapshot

Attributes	Description
Summary properties	
"Systemic reach"	Financial sector and main non-financial sectors
Forward-looking Properties	No (backward-looking)
Ease of use	Easy to use and update
Identification of linkages	Not identified
Likelihood (PD) or impact (LGD)?	PD
Coverage	
Sectors/Institutions	Deposit takers, other financial corporations, nonfinancial corporate sector, and households
Types of risk	Credit risk, market risk, and liquidity risk
Interpretation	
Main output	Capital adequacy, asset quality, earnings and profitability, liquidity, and sensitivity to market risk of the banking sector (core FSIs)
Other outputs	Soundness condition for nonbanking financial sectors, nonfinancial corporate sectors, and households as well as asset prices (encouraged FSIs)
Thresholds	No
Time horizon	Low frequency, backward-looking indicators
Data requirements	Aggregate data on balance sheet and P/L of banking sector, nonbanking financial corporations, and nonfinancial sectors; indebtedness of households, data for market liquidity and asset prices
Reference	IMF, 2006; Users: Sun, 2011

Methodology

FSIs consist of two sets of indicators, a core set of FSIs and an encouraged set of FSIs. The core set of FSIs covers banking sector, reflecting the central role of the banking sector in many financial systems. The encouraged set of FSIs covers additional FSIs for the banking sector as well as FSIs for key nonfinancial sectors and asset prices. The health of the financial sector can be analyzed by looking at levels and trends in FSIs. It should be noted, however, that interpreting developments in FSIs presents the following challenges:

Since FSIs are aggregated data, measures of dispersion should be monitored to analyze the vulnerability of the financial system.

FSIs allow continuous monitoring of strengths and vulnerabilities over time and show the current financial soundness of the financial system. They do not measure precisely the likelihood of, or resilience against, future shocks. Therefore, the analysis of FSIs should be strengthened by using higher frequency or more forward-looking tools.

Example

The website of FSIs (http://fsi.imf.org/) provides the following core set and encouraged set of FSIs of 100 countries to monitor the current financial soundness of their financial systems.

Financial Soundness Indicators: Core and Encouraged Sets

Core Set	
Deposit-takers	
Capital adequacy	Regulatory capital to risk-weighted assets; Regulatory Tier 1 capital to risk-weighted assets; Nonperforming loans net of provisions to capital
Asset quality	Nonperforming loans to total gross loans; Sectoral distribution of loans to total loans
Earnings and profitability	Return on assets; Return on equity; Interest margin to gross income; Noninterest expenses to gross income
Liquidity	Liquid assets to total assets (liquid asset ratio); Liquid assets to short-term liabilities
Sensitivity to market risk	Net open position in foreign exchange to capital
Encouraged set	
Deposit-takers	Capital to assets; Large exposures to capital; Geographical distribution of loans to total loans; Gross asset position in financial derivatives to capital; Gross liability position in financial derivatives to capital; Trading income to total income; Personnel expenses to noninterest expenses; Spread between reference lending and deposit rates; Spread between highest and lowest interbank rate; Customer deposits to total (noninterbank) loans; Foreign-currency-denominated loans to total loans; Foreign-currency-denominated liabilities to total liabilities; Net open position in equities to capital
Other financial corporations	Assets to total financial system assets; Assets to GDP
Nonfinancial corporations sector	Total debt to equity; Return on equity; Earnings to interest and principal expenses; Net foreign exchange exposure to equity; Number of applications for protection from creditors
Households	Household debt to GDP; Household debt service and principal payments to income
Market liquidity	Average bid-ask spread in the securities market; Average daily turnover ratio in the securities market
Real estate markets	Residential real estate prices; Commercial real estate prices; Residential real estate loans to total loans; Commercial real estate loans to total loans

XVII. Bank Health Assessment Tool (HEAT)

The HEAT is a tool for calculating a Bank Health Index (BHI) based on simple CAMELS-type ratings for each bank, including systemically important ones. It is simple to use and update and provides a measure of relative (but not absolute) health of a banking system. System-wide health, vis-à-vis a global peer group of banks such as the G-SIBs, can also be assessed by taking the aggregate of each variable for all banks in the system to derive system-wide BHIs, or by inputting system-wide ratios available from the Financial Soundness Indicators database.

Tool Snapshot

Attributes	Description
Summary properties	
"Systemic reach"	Bank-by-bank aggregation of CAMEL-type indicators, for systemically important banks
Forward-looking Properties	No (backward-looking)
Ease of use	Easy to use and update
Identification of linkages	Not identified
Likelihood (PD) or impact (LGD)?	PD
Coverage	
Sectors/Institutions	Deposit takers and other financial corporations
Types of risk	Solvency, credit and liquidity risk
Interpretation	
Main output	Bank Health Index for each bank that aggregates standardized versions of five financial ratios—capital adequacy, nonperforming loans ratio, return on assets, liquid assets ratio and leverage ratio.
Other outputs	—
Thresholds	No
Time horizon	Low frequency, backward-looking indicators.
Data requirements	Banks' financial statements from Bankscope, Bloomberg, or SNL.
Reference	Ong, Jeasakul and Kwoh (2012)

Methodology

For each bank, five financial ratios are calculated: capital adequacy (total equity or Tier 1 capital to Risk-weighted Assets), nonperforming loans to gross loans less ratio of provisions to gross loans, return on average assets, liquid assets to customer deposits and short-term funding, and tangible common equity to tangible assets. Each financial ratio is normalized around the system-wide (or all sample banks') mean and standard deviation over the three years to time t. The sum of the five standardized financial ratios is the BHI, relative to its peers. The BHI for a country's banking system compared to a global peer group would give the relative health of a banking system.

Example

The BHI for Spanish banks using end-2011 data was derived as a first-pass analysis of their relative soundness. The heat map subsequently generated using HEAT shows the differentiation in the soundness across banks within the Spanish system, as well as the evolution of the financial health of the institutions over time (see table). The heat map shows the system-wide distress in 2008, especially concentrated at the mid-sized to smaller banks. An overall system-wide indicator can be derived by averaging the asset-weighted BHIs.

Spain: Heatmap of BHI for Selected Banks

Institution	Cajas de Ahorros	Total Assets (In millions of euro) Latest	Overall Bank Health: Pre-Restructuring 2006	2007	2008	2009	Post-Restructuring 2010	2011
1 Santander S.A.		1,292,677	0.95	0.38	1.83	3.66	5.18	3.63
2 BBVA		622,359	2.81	2.88	1.08	2.19	4.94	3.48
3 BFA- Bankia		321,188			-3.92	-2.58	-4.48	-7.66
	Caja Madrid		0.62	5.13	-3.57	-3.02		
	Bancaja		0.29	-0.91	-4.26	-1.81		
	Caiza Laietana		-4.28	-8.04	-5.38	-4.34		
	Caja Insular		-2.88	-2.89	-4.73	-3.76		
	Caja de Avilla		-0.66	1.80	-4.23	-2.45		
	Caja Segovia		-0.81	-1.74	-4.09	-1.28		
	Caja Rioja		-0.94	-0.58	-1.16	-0.90		
4 Caixa Banca		281,554					2.46	1.92
	La Caixa		4.60	4.58	1.71	2.79	3.31	1.98
	Caixa de Girona		-0.10	-2.01	-3.88	-2.38		
5 Catalunya Caixa		77,049					-5.24	-7.41
	Caixa Catalunya		1.15	-2.01	-5.58	-4.01		
	Caixa Tarragona		-2.03	-3.53	-6.05	-4.15		
	Caixa Manresa		-1.43	-1.21	-3.45	-2.98		
6 Nova Caixa Galicia		76,133					-6.00	-4.37
	Caixa Galicia		0.18	-1.07	-4.55	-3.36		
	Caixanova		1.65	-0.83	-3.25	-2.33		
7 Unicaja	Unicaja	40,214	6.07	4.45	3.42	5.30	5.67	4.70
	Caja de Laen		1.94	1.81	0.76			
8 Unnim		28,924					-6.30	-6.02
	Caixa Sabadell		-3.39	-4.67	-5.00	-3.02		
	Caixa Terrassa		0.73	-0.43	-2.51	-3.51		
	Caixa de Manlleu		-6.55	-6.51	-6.09			
9 Kuxta		20,016	7.25	8.19	2.62	2.65	1.71	1.47
10 CAM	Caja Mdeiterraneo	74,478	-2.55	-2.91	-4.11	-1.92	-4.37	

Sources: Table 2 of Ong, Jeasakul and Kwoh, 2012.

XVIII. Thresholds Model

The Noise-to-Signal ratio relies on macroeconomic and financial balance-sheet data to select variables and corresponding thresholds that can signal the possibility of financial crisis materializing in the future. It is easy to use/update and has reasonable in-sample forecasting properties for systemic stress, working better in advanced countries than in emerging or developing economies.

Tool Snapshot

Attributes	Description
Summary properties	
"Systemic reach"	Financial system and economy as a whole
Forward-looking Properties	Good medium-term (1 to 5 years ahead) indicator of financial sector risk build-up for advanced countries. Somewhat weaker performance for emerging markets
Ease of use	Easy to use and update
Identification of linkages	Not identified
Likelihood (PD) or impact (LGD)?	PD
Coverage	
Sectors/Institutions	Financial sector as a whole. Can also cover alternative groups of institutions provided a group-specific measure of distress is available
Types of risk	Risk of distress for the financial system as whole
Interpretation	
Main output	Set of variables and corresponding thresholds which, in combination, produce early warning indicators of potential financial crisis
Other outputs	Type-I and Type-II errors, indicating the fraction of missed crisis relative to total crisis and the fraction of false signals relative to potential signals respectively. The noise-to-signal ratio captures the trade-off between the two types of errors
Thresholds	Change in credit-to-GDP increases 2 standard deviations above its historical mean in a given country
Time horizon	Good for predicting medium-term materialization of financial system-wide stress (1 to 5 years ahead)
Data requirements	Low- frequency macroeconomic and financial balance-sheet time series; requires a measure of materialization of stress in the system (Laeven and Valencia (2010)
Reference	Main: Borio and Drehmann, 2009; Users: IMF, 2011b

Methodology

The Noise-to-Signal Ratio (NSR) approach intends to select a set of macroeconomic and balance-sheet variables as well as their respective thresholds to form early warning indicators (EWI) of potential crisis. The methodology is implemented in five steps: (I) define a crisis indicator, a binary variable that assumes the value of 1 when a crisis occurs and 0 otherwise; (II) select one or more variables that can potentially forecast crisis; (III) calibrate various potential thresholds for each one of those variables; (IV) compute a binary variable called crisis signal, which assumes the value of 1 when a certain number (or all of the forecasters) move beyond their corresponding thresholds, and zero otherwise. A failure to signal a crisis that actually happens produces a Type-I error, whereas a false signal (a signal of 1 that is not followed by a crisis in the future) produces a Type-II error. (V) combine the different errors to compute the NSR as: $NSR = \frac{\pi_{II}}{1-\pi_I}$. The term π_{II} denotes the fraction of type-II errors (relative to total noncrisis observations), whereas π_I denotes the fraction of type-I errors (relative to total crisis observations). The lower the NSR better the trade-off between the two errors produced by the forecasting variables and their thresholds.

Example

Annual data on credit-to-GDP and a crisis indicator, covering 169 countries from 1970 to 2010 is used. Comparison between two alternative measures of credit and their corresponding thresholds as predictors of crises. The crisis indicator is based on updated data from Laeven and Valencia (2008). The table below (produced for illustrative purposes) shows the NSR for different lags of the forecasting variable and different thresholds, defined as the number of standard deviations (std) above historical average for each variable, calculated on a country-by-country basis. The lowest NSR in yellow suggests that a 2 std move in the credit growth presents the best trade-off between type-I and type-II errors 2 years before a potential crisis period. Hence, authorities in a given country should be alert about the possibility of a crisis materializing in the next two to three years if the credit-to-GDP change moves by 2 std or more.

		NSR	
Intensity of Change	**Lag**	**Credit-to-GDP Gap**	**Credit-to-GDP Change**
1 Std	**1**	**0.23**	**0.30**
	2	**0.27**	**0.31**
	3	**0.39**	**0.32**
2 std	**1**	**0.26**	**0.37**
	2	**0.36**	**0.22**
	3	**0.36**	**0.22**

Source: IMF staff estimate.

XIX. Macro Stress Tests

Macro stress tests provide quantitative analyses of system-level risks and vulnerabilities. FSAPs assess a range of risks in stress tests, within the broad categories of credit risk, market risk, liquidity risk, and contagion risk.

Tool Snapshot

Attributes	**Description**
Summary properties	
"Systemic reach"	Aggregation of core financial institutions
Forward-looking Properties	Not forward-looking in a sense that stress test is not based on prediction
Ease of use	Easy to use and update depending on employed methodologies
Identification of linkages	Partial identification of linkages depending upon the model
Likelihood (PD) or impact (LGD)?	LGD
Coverage	
Sectors/Institutions	Mainly banks, but nonbanking sector including insurance sector being increasingly covered
Types of risk	Credit risk, market risk, liquidity risk, and contagion risk
Interpretation	
Main output	Capital Adequacy Ratios (CAR) under "extreme but plausible scenario"
Other outputs	Nonperforming loans, loan-loss provisioning, Value-at-Risk, liquidity position, and net open currency position under "extreme but plausible scenario"
Thresholds	Regulatory capital requirement
Time horizon	Two to five year scenario being used
Data requirements	Balance sheet and P/L data of core financial institutions, real and financial data
Reference	Moretti, Stolz, and Swinburne, 2008

Methodology

Typical FSAP-style macro stress tests consist of four steps: (i) identification of specific vulnerability or concerns; (ii) construction of "extreme but plausible" stress scenario using macroeconomic model that links external shocks to macroeconomic variables; (iii) mapping of the stress scenario into financial institutions' balance sheets and income statements by bottom-up and/or top-down approach; and (iv) assessment of the resilience of the financial system by interpreting quantitative results.

FSAPs have addressed a range of risks in stress tests, within the broad categories of credit risk, market risk, liquidity risk, and contagion risk. In a typical stress test in credit risk models, NPLs or loan-loss provisions are modeled as a function of various macroeconomic variables. The analysis of market risks has used a range of different approaches. Interest rate risk analysis uses pricing and maturity gaps, duration, and value at risk. Exchange rate risk analysis focuses on net open positions. Stress tests for liquidity risk have assumed shocks to deposit and wholesale funding and overseas funding. Stress tests for contagion risk use data on uncollateralized interbank exposures to assess whether the failure of one bank induce failure in other banks.

It should be noted that stress tests have to be tailored to country-specific circumstances, as to the different types of risks and institutions to be subjected to stress testing, the type and size of shocks applied to the stress scenario, and data availability.

Example

Since the FSAP's inception in 1999, FSAPs have been carried out at least once and for many countries more than once, for over 130 countries—more than two thirds of Fund membership. A list of upcoming FSAPs and notes on stress test methodologies are available at the FSAP site (http://www.imf.org/external/pubs/ft/survey/so/2012/POL011312A.htm) and country FSAP document site (http://www.imf.org/external/NP/fsap/fsap.aspx).

XX. GDP AT RISK

The Systemic Risk Monitoring System (DNL-SRMS) forecasts systemic real and financial risks, using time series of indicators of financial and real activity. It is complex to use/update but has good out-of-sample forecasting properties for systemic stress.

Tool Snapshot

Attributes	Description
Summary properties	
Forward-looking Properties	Good out-of-sample forecasting abilities for systemic stress
Ease of use	Complex to use and update
Likelihood (PD) or impact (LGD)?	PD and LGD
Coverage	
Sectors/Institutions	Equity markets data by sector
Types of risk	Systemic real risk is defined as the worst predicted realization of quarterly growth in real GDP at 5 percent probability. Systemic financial risk is defined as the worst predicted realization at 5 percent probability of the market-adjusted equity return of a large portfolio of financial firms
Interpretation	
Main output	Forecasts of indicators of systemic real risk and systemic financial risk-based on the predicted density distribution of the underlying indicators
Other outputs	Systemic risk fan charts to summarize systemic real and financial risk prospects
Thresholds	Yes
Time horizon	Good for predicting near-term materialization of financial system-wide stress
Data requirements	A large set of quarterly time series of indicators of financial and real activity for each country, including equity markets data, financial, monetary and banking variables related to credit conditions, and price and real variables
Reference	De Nicolò and Lucchetta (2010)

Methodology

The *DNL-SRMS* is a set of forecasting models estimated in real-time based on developments of the methodology introduced in De Nicolò and Lucchetta (2010). The *DNL-SRMS* is currently implemented using large sets of quarterly time series of indicators of financial and real activity with data starting in 1980Q1 for 22 advanced economies.[5] It delivers at a country level:

Forecasts of indicators of *systemic real risk* and *systemic financial risk*, as well as forecasts of the distribution of GDP growth and an indicator of financial stress;

Absolute and relative risk ratings of forecasts of systemic real and financial risks;

Tail risk relative ratings of forecasts of indicators of key economic conditions;

Systemic real risk is measured by *GDP-at-Risk (GDPaR)*, defined as the worst predicted realization of quarterly growth in real GDP at 5 percent probability. *Systemic financial risk* is measured by an indicator of *Financial System-at-Risk (FSaR*), defined as the worst predicted realization at 5 percent probability of the *market-adjusted equity return* of a large portfolio of financial firms.

Forecasting of *GDPaR* and *FSaR* indicators is accomplished in three steps. *First*, a large set of *quarterly* financial and macroeconomic variables is modeled as a multivariate dynamic factor model. Estimated time series of *factors* summarize the joint dynamics of the series, and are used as *predictors* of GDP growth and the market-adjusted equity return of financial firms. *Second*, joint forecasts of factors, GDP growth and market-adjusted equity return of financial firms are generated by Vector Auto-Regressions (VAR). *Third*, 8-quarters ahead VAR forecasts of predictors are used to *forecast GDPaR* and *FSaR* via Quantile Auto-Regressions (QARs).

Example

De Nicolò and Lucchetta (2010) examines the out-of sample performance of the model, specifically assessing whether the model signals a decline in *GDPaR* prior to 2008Q4-2009Q1 in all G-7 countries.

The results show predicted changes in *GDPaR* and actual GDP growth go in the same direction for at least 1 quarter ahead within a three quarters' horizon (up to 2009Q1) in all countries. The out-of sample consistency of *GDPaR* forecasts with the future evolution of actual GDP growth for the most unpredictable event in decades suggests the potential usefulness of this model as a real-time risk monitoring tool.

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[5]The countries covered (listed by geographical areas) are the following. *North America*: Canada and the United States. *Asia/Pacific*: Japan, Korea, Australia and New Zealand. *Atlantic:* U.K. and Ireland. *Western Europe:* France, Belgium, and Netherlands. *Central Europe*: Germany, Austria, and Switzerland. *Southern Europe:* Italy, Spain, Portugal and Greece. *Northern Europe*: Denmark, Finland, Norway, and Sweden.

XXI. Credit to GDP-Based Crisis Prediction Model

This model computes a banking crisis probability measure focusing on an 'excessive' credit growth indicator. It evaluates non-linear effects by allowing the interaction between the latter and other risk factors including leverage, noncore liabilities, and asset prices. It also constructs conditional crisis signals and evaluates the performance of each risk factor as an early warning indicator.

Tool Snapshot

Attributes	Description
Summary properties	
"Systemic reach"	Banking sector
Forward-looking Properties	One to three year forecast horizon. Relatively good out-of-sample properties
Ease of use	Easy to update
Identification of linkages	The introduction of interactive risk factors allows the identification of amplification channels. For instance, credit to GDP growth contributes to systemic risk in combination with a 25 percent equity price growth
Likelihood (PD) or impact (LGD)?	PD
Coverage	
Sectors/Institutions	Banking sector
Types of risk	Credit risk, market risk, funding risk
Interpretation	
Main output	Time-varying banking crisis probability
Other outputs	Marginal effect on systemic risk from individual factor indicators, threshold values for risk factors; type I and type II forecast errors
Thresholds	Yes
Time horizon	Near to medium term predictive power
Data requirements	Banking crisis database from Reinhart and Rogoff (2010) or from Laeven and Valencia (2010); annual data from IFS, WEO, Haver, and Bloomberg
Reference	**Lund-Jensen, 2012; Users: IMF, 2011b**

Methodology

The model assumes that the binary banking crisis variable $y_{i,t}$, evaluated for country *i* at time *t*, is drawn from a Bernoulli distribution that depends on *k* systemic risk factors $x_{i,t-h}$ lagged *h* periods. The probability of a banking crisis is specified as:

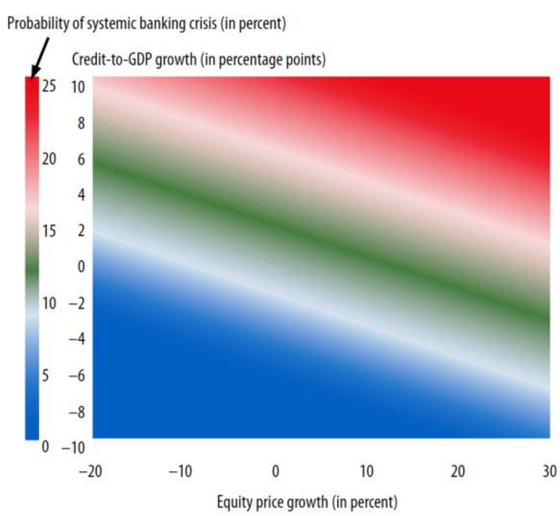
$$\Pr\left(y_{i,t} = 1 \middle| x_{i,t-h}; \alpha_i, \beta\right) = \Phi\left(\alpha_i + x'_{i,t-h}\beta\right)$$

where Φ is the cumulative density of a standard normal distribution (probit) or a standard logistic distribution (logit). The underlying risk factors include excessive credit growth measured by credit-to-GDP growth or credit-to-GDP gap, equity and house price inflation, banking sector leverage (private credit to deposit ratio), noncore liabilities (foreign banking sector liabilities to M2), and fluctuations in the real effective exchange rate. In the single factor analysis, credit-to-GDP growth features as the main contributing factor to systemic risk up to three years ahead. In the multivariate specification, the combination of credit-to-GDP gap, leverage, and equity price inflation appear as the main determinants of systemic risk.

This tool also allows backing out a crisis signal threshold for alternative modeling specifications with associated critical values for the underlying risk factors. It shows that combining several risk factor indicators greatly improves the accuracy of the crisis signal.

Example

Using annual panel data for 36 countries over the period 1975-2010 featuring 26 banking crisis observations, the linear combination of one-period lagged credit-to-GDP growth and two-period lagged equity price growth yield the banking crisis probability surface that is depicted below.



Source: IMF (2011b).

XXII. Crisis Prediction Models

This methodology identifies a set of 23 to 25 indicators that are correlated with financial, fiscal, or growth crisis events. For each indicator, a threshold value minimizing its noise-to-signal ratio is obtained, and a weight assigned based on its predictive power. A composite weighted indicator is thus constructed and mapped into a crisis probability defined as the percentage of crisis observations conditional on the composite indicator flagging.

Tool Snapshot

Attributes	Description
Summary properties	
"Systemic reach"	Financial sector, public sector, real sector
Forward-looking Properties	One year leading indicator
Ease of use	Requires a nonparametric algorithm
Identification of linkages	Not identified
Likelihood (PD) or impact (LGD)	PD
Coverage	
Sectors/Institutions	Financial sector, public sector, real sector
Types of risk	Financial Crisis, Sudden Fiscal Consolidation, Growth Slowdown
Interpretation	
Main output	Probability of a systemic financial, fiscal or growth crisis
Other outputs	Composite vulnerability indicator; individual financial, real, and fiscal indicators, their threshold values, and their associated weights
Thresholds	Yes—specific thresholds for each indicator
Time horizon	Near term predictive power
Data requirements	Annual data from WEO, IFS, OECD, Bankscope, Worldscope, and Bloomberg
Reference	IMF-FSB, 2010

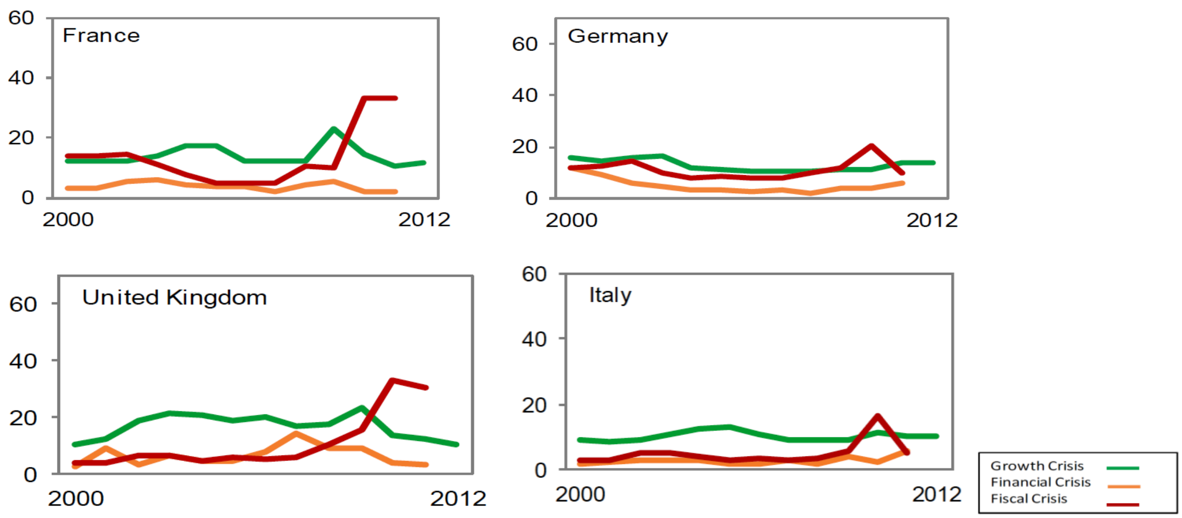
Methodology

The construction of a crisis prediction measure requires two steps. First, a crisis event is defined. A financial crisis is based on the database provided by Laeven and Valencia (2008). A fiscal crisis is defined as an abrupt fiscal consolidation within a year of at least 2.5 percent of cyclically adjusted primary balance from a negative value of at least 2.5 percentage points.

A growth slowdown is determined by the lowest 5 percentile of the historical distribution of the gap between contemporaneous growth and a 5-year rolling average.
Second, a set of medium-term (5-year rolling average) and near-term variables (lagged one period) are identified as potential indicators. Under the noise-to-signal nonparametric approach, a threshold value minimizing the ratio of false alarms to true signals is calibrated for each indicator, and a weighted composite indicator constructed where an indicator's weight correspond to its forecasting ability. The value of the composite indicator is then mapped to a crisis probability defined as the percentage of crisis observations for which the composite indicator exceeds its critical threshold.

Example

A crisis prediction model has been used in October 2011 to identify key vulnerabilities and assess systemic risk in advanced economies. The graph below shows a medium risk of growth slowdown (a probability above 10 percent) for France, Germany, Italy and United Kingdom. Moreover, the results suggest that France and United Kingdom feature an elevated risk of fiscal crisis (a probability above 20 percent). On the other hand, financial risk, net of sovereign distress spillover or contagion effects, remains contained.



Source: IMF-FSB (2010), and Vulnerability Exercise for Advanced Economies (2011), October.

XXIII. DSGE Model

DSGE models can trace movements of numerous macroeconomic and financial variables in response to alternative sources of shocks. A calibrated model can be used to analyze the macro-financial effects of various macroprudential policy instruments, like countercyclical capital buffers and loan-to-value ratio caps. It only covers procyclicality and not interconnectedness, and requires considerable experience to run.

Tool Snapshot

Attributes	Description
Summary properties	
"Systemic reach"	Banks, nonfinancial corporations, households
Forward-looking Properties	Counterfactual analysis
Ease of use	Difficult to use (requires experience)
Identification of linkages	Provides in-depth understanding of interactions and shock transmission across sectors
Likelihood (PD) or impact (LGD)?	LGD
Coverage	
Sectors/Institutions	Banks, nonfinancial corporations, households
Types of risk	Procyclicality stemming from shocks related to: real estate prices, lax lending standards, productivity
Interpretation	
Main output	The macro-financial impact of various shocks with and without macroprudential policies
Other outputs	Leading indicators of future financial instability
Thresholds	Not available
Time horizon	Flexible.
Data requirements	Various, depending upon calibration requirements.
Reference	Benes and others, 2010; Users: IMF, 2011b.

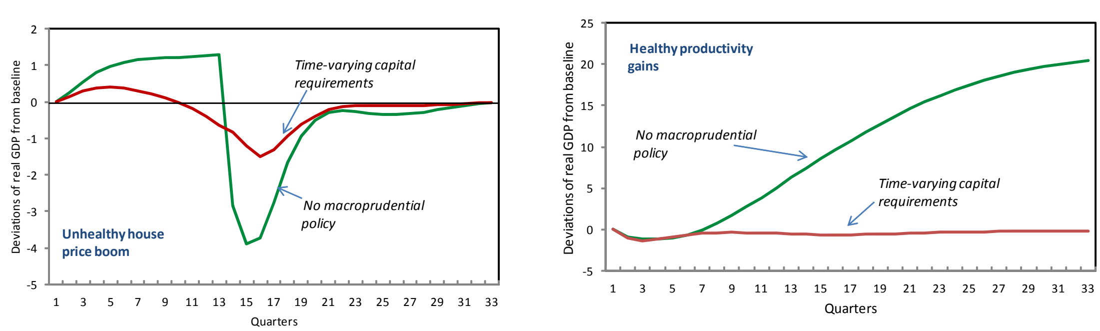
Methodology

The model embeds a banking sector along with a new-Keynesian model of the real sector. Key features of the banking sector include: the strong role of the balance sheets of both banks and nonfinancial borrowers in the propagation of shocks, and 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. The macroprudential concern stems from the presence of the aggregate risk. There are many flexible parameters to mimic different types of economies—extent of foreign-currency lending, 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 the banks can raise fresh equity capital in financial markets.

Example

The DSGE model was used in IMF (2011b) to assess the effects of countercyclical capital buffers in the presence of two types of shocks: shocks related to (healthy) productivity gains that do not lead to crisis, and shocks leading to (unhealthy) a house price boom that is followed by a crisis. The model shows the effects of macroprudential policy on the real economy under the two shock scenarios. If there is an unhealthy house price boom that has a high probability of ending in a crisis, then countercyclical capital buffers (CCBs) can successfully cushion the crisis-effects on real GDP levels (left figure below). However, if there is a process of healthy productivity gains and policymakers mistake it for an unhealthy process (like a house price boom), then macroprudential policy can do permanent damage and lower the real GDP level indefinitely (right figure below).

Effects of Macroprudential Policy on Real GDP level: Countercyclical Capital Buffers on Two Types of Shocks



Source: IMF, 2011b

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.

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