

## B ANALYTICAL MODELS AND TOOLS FOR THE IDENTIFICATION AND ASSESSMENT OF SYSTEMIC RISKS

*The identification and assessment of systemic risks is a core function of macro-prudential supervision. There are four broad approaches for analytical models and tools that can support this function. The first three each aim to detect early one of the three main forms of systemic risk, namely the endogenous build-up and unravelling of widespread imbalances, exogenous aggregate shocks and contagion. First, early-warning models and indicators use information in current data in order to signal the presence of emerging imbalances and risks without adding exogenous shocks that are not priced in by the market. Second, macro-stress-testing models are used to assess the resilience of the financial system against extreme but plausible scenarios of widespread exogenous shocks, irrespective of whether current market data give a particular weight to them. Third, contagion and spillover models assess the transmission of instability among financial intermediaries and among financial markets to the extent that the sources are not common. Financial stability indicators, the fourth approach, display the current state of systemic instability in order to, for example, identify the presence of crises. The specific tools underpinning these approaches are broadly available, although further research efforts are also necessary.*

### INTRODUCTION

The understanding of systemic risk is at the centre of macro-prudential supervisory and regulatory policies. Identifying and assessing systemic risks requires a broad and deep information basis and a wide range of tools to process the relevant information. Ingredients for meeting these requirements include market intelligence, plain data analysis and analytical models and tools.

While all these ingredients are equally important, this special feature focuses on the

analytical models and tools that can be used to interpret the information collected through market intelligence and statistics. The objective is to characterise the main broad approaches that are available and to illustrate with selected examples what macro-prudential policy-makers can learn from them.

The first section recalls some main elements of the phenomenon of systemic risk that analytical models and tools need to address. The remainder of the feature is organised into four sections, one on each of the main broad analytical approaches that can be used, followed by a concluding section.

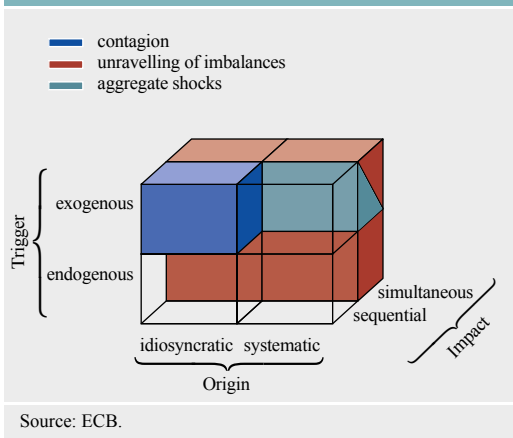
### IDENTIFICATION AND ASSESSMENT OF SYSTEMIC RISKS IN THE PROCESS OF MACRO-PRUDENTIAL SUPERVISION

Systemic risk can be described as the risk that financial instability becomes so widespread that it impairs the functioning of a financial system to the point where economic growth and welfare suffer materially. The literature has identified three “forms” of systemic risk, namely contagion risk, the risk that widespread imbalances that have built up over time unravel abruptly, and the risk of macro shocks causing simultaneous failures. The three forms can be summarised in a “systemic risk cube” displayed in Chart B.1, which distinguishes their origins, the nature of triggers unleashing a systemic event and their impact.<sup>1</sup>

There are four broad analytical approaches with which systemic risks and instability can be identified and assessed. First, coincident indicators of financial stability measure the current state of instability in the financial system. Second, early-warning signal models can be used to derive indications about the likelihood and severity of systemic events and crises

<sup>1</sup> The three forms of systemic risk and the “cube” characterisation are based on J.C. Trichet, “Systemic risk”, Clare Distinguished Lecture in Economics and Public Policy, Cambridge University, December 2009; O. de Bandt, P. Hartmann and J.L. Peydro, “Systemic risk: an update”, in A. Berger et al. (eds.), *Oxford Handbook of Banking*, Oxford University Press, 2009; and ECB, “The concept of systemic risk”, *Financial Stability Review*, December 2009, which contain more detailed discussions.

Chart B.1 Systemic risk cube



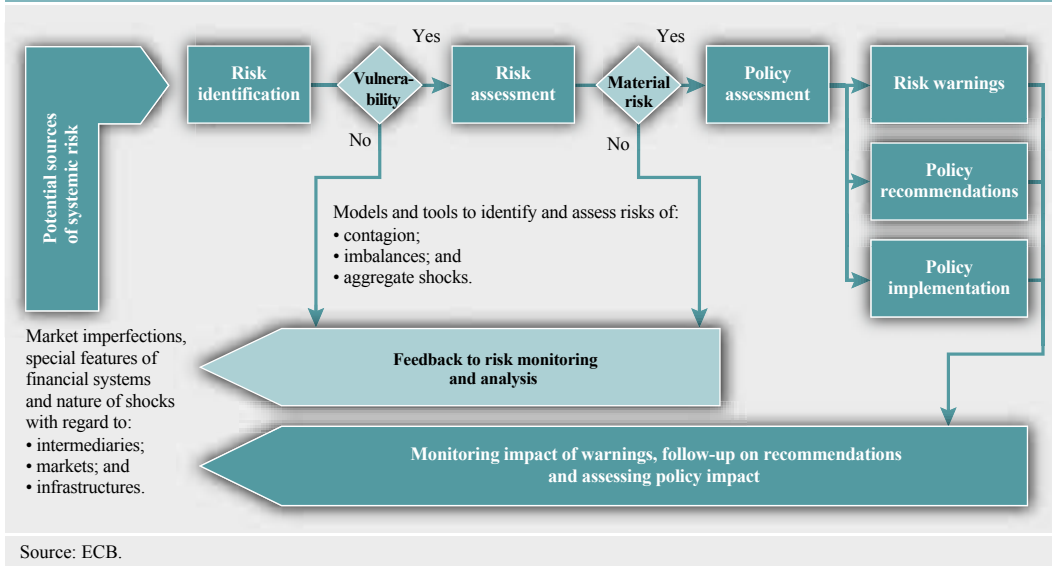
to widespread crises and about which the macro-prudential supervisor should thus be concerned. Notably, early-warning signal models can be used as a means to identify early the build-up of imbalances that may become so severe and widespread that they typically lead to a crisis in the future. Macro-stress-testing models can serve to identify aggregate shocks that are so severe that they would cause a systemic crisis. Finally, contagion models can be used to assess which financial intermediaries' failure could lead to the spreading of instability. In practice, however, specific models and tools can also serve a variety of macro-prudential purposes, as some examples chosen for this special feature will illustrate.

happening in the future. Third, macro-stress-testing models can be employed to assess the resilience of the financial system to extreme but plausible aggregate shocks. Fourth, contagion and spillover models can serve as means to assess how resilient the financial system is to the transmission of originally more limited financial shocks across intermediaries and markets.

The last three approaches are designed to allow for an early identification and assessment of the forms of systemic risk that can lead

The approaches for a forward-looking identification and assessment of systemic risks also fit well into the main steps that a macro-prudential supervisory body would logically follow (see Chart B.2). Such a body could structure the risks according to an economic framework such as that illustrated by the "systemic risk cube" and explained in greater detail in Special Feature B of the December 2009 FSR (see left-hand side of the chart). The process begins with risk identification. Early-warning signal models and indicators, in particular, are

Chart B.2 Role of analytical models and tools for systemic risk in the macro-prudential oversight process



designed for this purpose. Some of these tools can also assign probabilities to specific shocks or systemic events. These probabilities can be one input into the ranking of risks for the second step of the supervisory process, namely, the assessment of risks. For the assessment, macro-stress-testing models are particularly useful. These models can take the materialisation of the most plausible risk scenarios as input and then simulate the severity of the impact on the financial system. Similarly, contagion and spillover models can be used to evaluate the impact of specific failures on the financial system using, for example, counterfactual simulations.

The result of this process is, ideally, a prioritisation list of the most relevant risks, which consists of a list of detected risks, probabilities of each of these risks materialising, systemic losses given default for each of them, expected system losses and expected losses in macroeconomic output in the case of these risks materialising.

Based on such a process of risk identification and assessment, macro-prudential supervisory bodies would assess policy actions as early preventive measures. They could consider giving warnings about risks, recommending the use of policy instruments by other bodies or implementing policies with their own instruments. The assessment of different policies can again be supported by, inter alia, analytical models. Some of them may be extensions of the models and tools discussed in this special feature, while others will be different models. Analytical models to assess different macro-prudential policies are not the subject of this special feature.

## FINANCIAL STABILITY INDICATORS

Financial stability and systemic risk indicators measure the contemporaneous level of instability and systemic stress. They can be direct indicators, such as those for asset price volatilities, debt yield spreads, credit default swap spreads, etc., or indicators derived from analytical models, such as those for default probabilities derived from credit risk models. A full macro-prudential

analysis requires financial stability indicators to be available for each systemically relevant intermediary, market and market infrastructure, as well as for combinations of these components, at the level of financial sub-sectors or the financial system as a whole.<sup>2</sup>

The example given below is a new composite indicator of systemic stress (“CISS”) developed at the ECB (see Chart B.1). CISS covers money, bond, equity and foreign exchange markets, as well as financial intermediaries, a novel feature in comparison with previous composite indicators of this kind. For each of these five components, stress is measured through several sub-measures involving volatilities, cumulative price declines, risk spreads or recourse to central bank emergency facilities. Each input is normalised by replacing observations with their quantile statistic,<sup>3</sup> so that the overall index ranges from 0 (no stress) to 1 (extreme stress in all components at the same time). The aggregation of the five components into one number is weighted by the correlation between them, which brings in the systemic component – another novel feature of this indicator.<sup>4</sup>

2 Overviews of financial stability indicators have, for example, been provided in W.R. Nelson and R. Perli, “Selected indicators of financial stability”, in *Risk Measurement of Systemic Risk*, Bank of Japan, ECB and Federal Reserve Board, 2007, and in many central bank financial stability reports (including the ECB’s FSR).

3 For example, if – at a specific point in time – an input variable has reached its 95th highest value in a sample of 100 observations, then this observation is transformed into a value of 0.95.

4 The time-varying correlations across the different sub-components are estimated as exponentially weighted moving averages (EWMA) with a constant decay factor of 0.93. EWMA are widely applied by practitioners in the calculation of the value at risk (VaR) (see K. Cuthbertson and D. Nitsche, *Quantitative Financial Economics*, 2<sup>nd</sup> edition, 2004). The estimated correlations tend to display a relatively stable path over time, but still react sufficiently strongly to the arrival of new information. For more details about the calculation of, and the data used in, CISS, see D. Hollo, M. Kremer and M. Lo Duca, “CISS – a composite indicator of systemic stress in the financial system”, 2010, available at [www.ssrn.com](http://www.ssrn.com). The ECB and other policy authorities have also developed other composite financial stability indicators (see R. Caldarelli, S. Elekdag and S. Lall, “Financial stress, downturns, and recoveries”, *IMF Working Paper Series*, WP/09/100, International Monetary Fund, 2009; M. Illing and Y. Liu, “Measuring financial stress in a developed country: an application to Canada”, *Journal of Financial Stability*, 2006; C.S. Hakkio and W.R. Keeton, “Financial stress: what is it, how can it be measured, and why does it matter?”, *Economic Review*, Federal Reserve Bank of Kansas City, 2009; and Box 1 in ECB, *Financial Stability Review*, December 2009).

**Chart B.3 Composite indicator of systemic stress (CISS)**

(Jan. 1999 – May 2010)



- 1 peak of "dot.com bubble"
- 2 11 September 2001
- 3 Enron bankruptcy
- 4 Iraq War
- 5 WorldCom bankruptcy
- 6 subprime ABS downgrades
- 7 reported problems in banks' investment and hedge funds
- 8 Lehman Brothers' bankruptcy
- 9 press focus on public debt

Sources: Thomson Reuters Datastream, ECB and ECB calculations.

Chart B.3 suggests that the CISS identifies the crisis of the last three years as the only truly systemic financial crisis of the last decade. In the autumn of 2008, around the time of the Lehman Brothers' bankruptcy, the indicator even approaches its maximum level of 1. By August 2007, the extreme stress was already more widespread than in previous periods of tensions, for example after 11 September 2001 or after the WorldCom bankruptcy. It should be noted, however, that the earlier years of the last decade were relatively tranquil and that further experience with this indicator needs to be gained, and further refinements tested and potentially incorporated over time, before more reliable conclusions can be drawn.

The use of such financial stability and systemic risk indicators by macro-prudential bodies is justified by their typical task of identifying systemic risks and issuing warnings about heightened risks. Moreover, the availability of indicators of systemic stability can serve as an input for identifying states of emergency.

An advantage of these indicators is that they can be developed for all systemically relevant

intermediaries and markets. Moreover, the set of indicators can be extended relatively swiftly and flexibly, depending on the specific issues of interest at a given point in time, and in response to innovation and structural change in the financial system. This is why macro-prudential authorities need to have a comprehensive set of financial stability indicators at their disposal and to continuously review it for extensions and updates. A challenge is that most of these indicators are partial in nature, so that they do not convey an overall view. This problem can be reduced to some extent by the use of composite indicators such as the CISS. However, composite indicators are relatively rough by nature, and thus share specific problems that limits their comparability and interpretability, such as the wide-ranging freedom of choice as to the selection of both the input series and the aggregation method. The partial nature of financial stability indicators also poses another challenge in that they are often not informative about the origins and transmission channels for widespread instability. Since many of them are coincident indicators (as is the CISS above), it also needs to be kept in mind that they are not designed to predict systemic instability in the future, which is rather the role of early-warning signal models and indicators.

#### EARLY-WARNING SIGNAL MODELS AND INDICATORS

Early-warning models and indicators are designed to predict financial instability that may emerge in the future and identify emerging vulnerabilities. As for the models, an index of bubble, imbalance, distress or crisis is typically defined first. Then, an empirical analysis is undertaken to identify variables that predict the index. Once variables are found which forecast the index well, these variables are monitored with respect to thresholds. Simple signalling approaches, for example, use single variables and derive optimal thresholds in terms of a percentile of their own distribution. More advanced approaches, such as limited dependent variable estimations or Markov-switching models, exploit a set of variables to estimate the probability of a

systemic event over a specific future horizon. In case the variables come close to, or exceed, a threshold, or when the crisis probability exceeds a certain level, one speaks of a vulnerability that implies a significant risk that a systemic event may occur in the future. The performance of an early-warning signal model can be assessed on the basis of the frequency of false alarms (type-I errors) and missed crises (type-II errors), compared with correctly predicted crises and correctly identified tranquil periods.

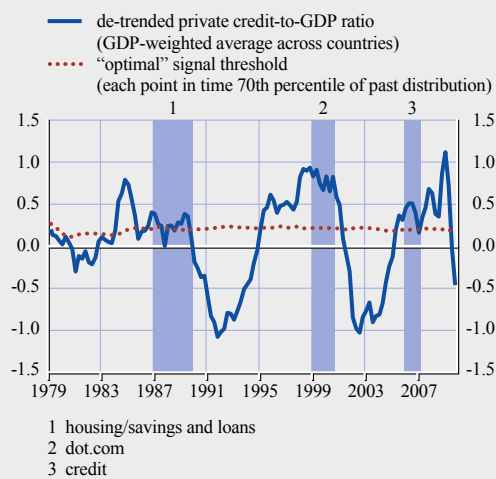
Early-warning indicators are the right-hand side variables in the models. They can also be used independently as simple indicators. They often compare current asset prices, balance-sheet relationships (such as leverage) or macroeconomic variables with estimates of their equilibrium levels. These levels can be estimated with economic models, with statistical models that extract, for example, “principal components” or through long-term averages of past data. Significant deviations of current observations from equilibrium levels are taken as signals for imbalances or vulnerabilities that could lead to crises in the future. Macro-prudential bodies need a comprehensive framework of early-warning models and indicators, so that no part of the financial system is excluded and warning signals across them are coherent.<sup>5</sup>

The example chosen in this special feature is the “global” credit-to-GDP gap as an early-warning indicator of widespread asset-price misalignments, the unravelling of which is associated with pronounced economic downturns. This indicator, defined as the de-trended and GDP-weighted average across 18 OECD countries, is shown as the blue line in Chart B.4 for the period from 1979 to late 2009. The shaded areas mark periods in which equity and mortgage prices in a larger number of industrial countries moved significantly above trend and in which their correction was associated with an extended period of growth below potential (“costly” misalignments).

The dashed red line is a time-varying signal threshold, which is optimally derived as the

**Chart B.4 “Global” credit gap as an early warning signal of “costly” asset price misalignments**

(Q1 1979 – Q4 2009)



Sources: IMF, BIS and ECB calculations.

Note: The blue shaded areas refer to widespread mortgage/equity boom episodes (more than eight countries with 1.75 standard deviations above trend), which proved “costly” (i.e. were followed by three years of GDP growth 3 p.p. below potential).

70th percentile of the past distribution of the credit gap series. When the solid blue line moves above the dashed red line, a signal is given that a costly boom-bust cycle is building up.<sup>6</sup> The indicator exceeded the threshold before each of the three major asset price misalignments, namely that at the end of the 1980s, the dot.com bubble and the boom preceding the latest crisis. With respect to this latter cycle, the “global” credit gap would have started issuing warning signals as early as mid-2005. Thus, policy-makers paying attention to such an indicator could have taken some corrective measures in advance.<sup>7</sup> Moreover, an interesting result of the underlying research is the degree of commonality

<sup>5</sup> For a more wide-ranging overview of early-warning techniques, see, for example, M. Chui and P. Gai, *Private Sector Involvement and International Financial Crises. An Analytical Perspective*, Oxford University Press, 2005.

<sup>6</sup> See L. Alessi and C. Detken, “‘Real time’ early warning indicators for costly asset price boom/bust cycles: a role for global liquidity”, *Working Paper Series*, No 1039, ECB, March 2009. Other examples of early warning indicators are described in ECB, “Indicators of financial distress in mature economies”, *Financial Stability Review*, June 2005; ECB, “Assessing the determinants of financial distress in French, Italian and Spanish firms”, *Financial Stability Review*, June 2005.

<sup>7</sup> This is also in line with other research highlighting the usefulness of credit gaps as early-warning indicators

of such severe asset price cycles across countries and the superiority of “global” and aggregate indicators over domestic indicators.

The use of early-warning signal models by macro-prudential bodies is also justified by their tasks in risk identification and early risk warnings. These indicators are particularly useful for the identification of the build-up of widespread imbalances (see the red parts in Chart B.1). They show the information that market variables contain about risks for the future. Such indicators would also integrate well in the newly emerging global set-up for macro-prudential oversight, such as the early warning exercises jointly undertaken by the Financial Stability Board and the International Monetary Fund.

They have to be used cautiously, however, since there are some significant challenges. First, in the past, early-warning models have rarely predicted new crises. While the new generation of models seems to have improved, predicting the exact timing of a crisis remains an extremely difficult task. Second, optimal early-warning models will probably vary for countries with different financial structures. In an international context, this raises the challenge of how they can be aggregated and how the signals for different countries can be made comparable. Third, early-warning indicators based solely on market information should always be complemented with information that the market is not pricing in, in order to capture vulnerabilities that are less obvious.

### MACRO-STRESS-TESTING MODELS

In contrast to early-warning models, stress-testing models do not take market expectations regarding the likelihood and severity of shocks as a given, but allow supervisory authorities to assume extreme but still plausible shocks and assess their consequences for different entities, also taking the propagation of the shock into account. The basic idea is borrowed from risk management, where the loss potential of specific portfolios can be assessed for

extreme market conditions (micro-stress-testing). Macro-prudential supervisors are particularly interested in macro-stress tests, where the banking system, or the financial system more broadly, is the object of interest. They can be particularly useful for assessing how resilient the system is against various adverse scenarios, even though they have not (yet) materialised in practice. This allows authorities to take early corrective action if the resilience is judged not to be high enough.

A macro-stress-test for banks, for example, consists of several inputs. First, an adverse macroeconomic (or macro-financial) downturn scenario needs to be defined on hypothetical grounds, or estimated from tail density forecasts of a macroeconometric model. Second, for every bank’s loan book, the adverse scenario impact needs to be linked to the probabilities of default (PDs) and losses given default (LGDs) of the loans.<sup>8</sup> Expected losses can then be calculated and comparisons with capital can be used to see whether and how many banks fail as a consequence.<sup>9</sup>

The use of macro-stress-testing frameworks by macro-prudential bodies is also justified by their task to assess and warn about systemic risks. In particular, by simulating losses and failures for different scenarios, they contribute to the prioritisation of different risks and potential policy responses such as the need for additional capital.

<sup>8</sup> Expected losses are calculated as “loan exposure at default” multiplied by PD multiplied by LGD.

For an overview of macro-stress-testing techniques, see, for example, M. Sorge, “Stress-testing financial systems: an overview of current methodologies”, *BIS Working Paper Series*, No 165, Bank for International Settlements, December 2004.

<sup>9</sup> See Section 4.2 in ECB, *Financial Stability Review*, December 2009, for a recent example, and for the methodology, see ECB, “Global macro-financial shocks and corporate sector expected default frequencies in the euro area”, *Financial Stability Review*, June 2007; ECB, “Assessing portfolio credit risk in a sample of euro area large and complex banking groups”, *Financial Stability Review*, June 2007; ECB, “Assessing credit risk in the loan portfolios of euro area large and complex banking groups”, *Financial Stability Review*, December 2007; and O. Castrén, T. Fitzpatrick and M. Sydow, “Assessing portfolio credit risk changes in a sample of EU large and complex banking groups in reaction to macroeconomic shocks”, *Working Paper Series*, No 1002, ECB, February 2009.

One of the main challenges of macro-stress-testing in general, besides data availability, is the definition of appropriate stress scenarios. Finding the right balance between plausibility and severity is not always straightforward. Moreover, stress-testing frameworks are not single coherent economic models. They are typically made up of a combination of separate modules. There is a lack of appropriate general equilibrium models capturing all the relevant relationships. Thus, simple reduced-form models are often used in this context. Frequently, non-bank intermediaries are not captured either. Last, there are no coherent macro-stress-testing models that take the two-way interaction between the financial system and the economy at large into account. Once the impact of a macro-scenario on the banking system has been simulated, the process stops.

#### CONTAGION AND SPILLOVER MODELS

Contagion and spillover models mainly serve to assess the cross-sectional transmission of financial instability. They are designed to measure the likelihood that, and extent to which, the failure of one or several intermediaries could cause the failure of other intermediaries or that the crash of one or several financial markets could lead to crashes of other markets. Two broad approaches have been used for this purpose, namely estimations of the extreme dependence of negative asset returns and counterfactual simulations using balance-sheet data. In the first approach, the extent to which a large loss of market value or a large increase in default probability, as incorporated in market prices, leads to further such losses or increases is considered after checking for common factors. The second approach simulates whether the failure of certain intermediaries would lead to losses by other intermediaries, which would erase their capital, thus causing further failures. If the initial failure or crash is solely responsible for subsequent failures or crashes, then one speaks of contagion. If it is not possible to test for confounding common factors, then the term spillover is often used.<sup>10</sup>

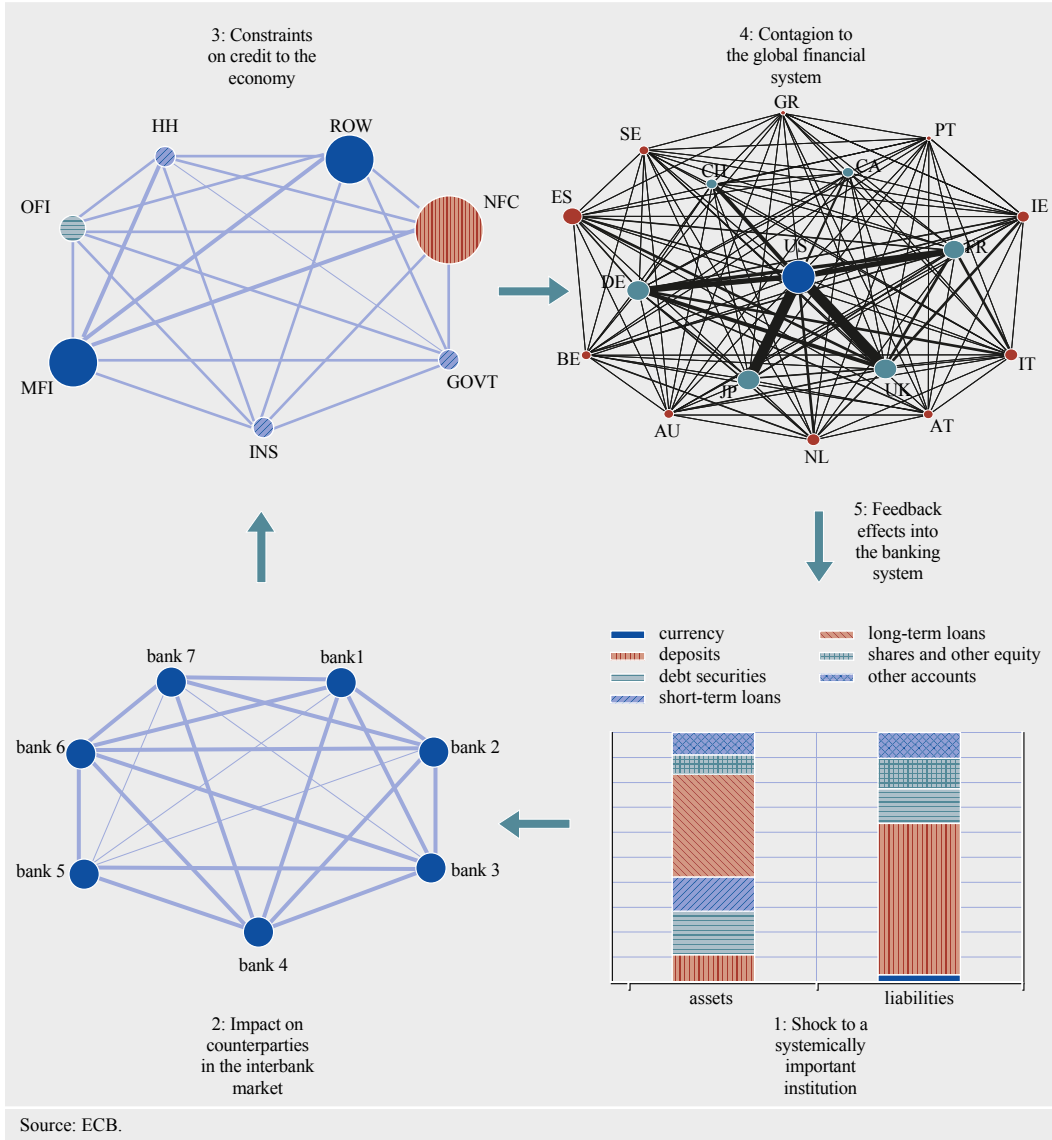
The example chosen for this special feature considers a spillover analysis that goes from the micro to the aggregate level, using the financial accounts in the ECB's euro area accounts. These data provide detailed information on the specific counterparties of the instruments issued by a given sector (the "who-to-whom" accounts). Once the bilateral exposures have been calculated, a network connecting all sectors in the financial system can be constructed. Chart B.5 illustrates shock propagation and spillover channels on the basis of a network of balance-sheet exposures. A shock to a systemically important institution will have an impact on its counterparties in the interbank market (see the lower left quadrant). This leads to credit constraints in the overall economy and, ultimately, to contagion effects in the global financial system, with possible feedback effects to the banking system (see the upper quadrants).<sup>11</sup>

The use of contagion and spillover models is again justified by the task of macro-prudential bodies to identify and assess systemic risks early and to warn about them (see the blue part in Chart B.1). They show and quantify transmission channels of instability across intermediaries, markets and market infrastructures, addressing externalities and also helping to identify systemically important intermediaries and markets. The specific flow-of-funds approach illustrated above also allows transmissions to the economy at large to be considered, because

10 For general reviews of contagion models, see, for example, O. de Bandt et al., op. cit.; C. Upper, "Using counterfactual simulations to assess the danger of contagion", *BIS Working Paper Series*, No 234, Bank for International Settlements, 2007; or ECB, "Financial market contagion", *Financial Stability Review*, December 2005. Special Feature D in this FSR discusses in depth one specific approach to assessing contagion risk based on network techniques.

11 For more details and further analysis, see Special Feature D in this FSR and ECB, "Balance sheet contagion and the transmission of risk in the euro area financial system", *Financial Stability Review*, June 2009; O. Castrén and I. Kavonius, "Balance sheet interlinkages and macro-financial risk analysis in the euro area", *Working Paper Series*, No 1124, ECB, December 2009. For a more advanced contagion analysis on the basis of euro area accounts data, see Box 13 in Section 4.2 of this FSR.

Chart B.5 Assessing shock propagation and contagion channels



the data link, inter alia, financial sub-sectors with the household, non-financial firm and government sectors.

Despite their usefulness in the above senses, contagion and spillover models also pose significant challenges. In particular, most of them do not capture endogenous reactions of market participants that could be present during crises, such as the amplification of instability through fire sales. Second, there are

data limitations with respect to access to, and the availability of, exposure data among banks and non-bank intermediaries. In addition, the few approaches that capture effects on the real economy, such as the flow-of-funds analysis presented above, may not give the full picture on them as only a sub-set of relevant instabilities and transmission channels is covered. Last but not least, available models do not distinguish well between contagion and the unravelling of imbalances.



## CONCLUDING REMARKS

One conclusion from the overview of approaches, models and tools in this special feature is that a broad analytical toolkit to support the new macro-prudential policy bodies in terms of risk identification and risk assessment is available. At the same time, further research efforts to improve and extend available models and tools are justified. For example, new financial stability and early-warning indicators need to be developed in response to financial innovation and structural change in the financial systems. Macro-stress-testing models need to be made more consistent and would benefit from the incorporation of non-bank intermediaries and new theoretical frameworks that reflect the two-way relationship between financial systems and the broader economy. Finally, contagion models would improve if they incorporated some amplification mechanisms that may play a role in actual stress situations and could better distinguish contagion from the unravelling of imbalances (see Chart B.1).

While it is necessary to use analytical models and tools for macro-prudential supervision, their precision and reliability should not be overstated. Each model or analytical tool relies on specific assumptions, as well as on the reliability and availability of the data. This special feature illustrated limitations and challenges in the use of various approaches. On the one hand, this has highlighted the need for future research efforts. On the other hand, it has also highlighted that market intelligence, regular data analysis, judgement and the experience of decision-makers are as important as the use of analytical models.