

C SYSTEMIC RISK METHODOLOGIES

The financial crisis has illustrated the importance of timely and effective measures of systemic risk. The ECB and other policy-making institutions are currently devoting much time and effort to developing tools and models which can be used to monitor, identify and assess potential threats to the stability of the financial system. This special feature presents three such models recently developed at the ECB, each focusing on a different aspect of systemic risk. The first model uses a framework of multivariate regression quantiles to assess the contribution of individual financial institutions to systemic risk. The second model aims to capture financial institutions' shared exposure to common observed and unobserved drivers of financial distress using macro and credit risk data, and combines the estimated risk factors into coincident and early warning indicators. The third model relies on standard portfolio theory to aggregate individual financial stress measures into a coincident indicator of systemic stress.

INTRODUCTION

An understanding of systemic risk is central to macro-prudential supervisory and regulatory policies. Quantitative measures of systemic risk can be helpful in identifying and assessing threats to financial stability. In the context of the great complexity of systemic risk and the need to formulate well-targeted policy responses, it has proven useful to distinguish three main forms of systemic risk, as described, for example, by the President of the ECB and in previous FSR special features.¹ First, contagion risk refers to an initially idiosyncratic problem that becomes more widespread in the cross section, often in a sequential fashion. Second, financial imbalances such as credit and asset market bubbles that build up gradually over time may unravel suddenly, with detrimental effects on intermediaries and markets more or less simultaneously. Third, shared exposure to financial market shocks or adverse macroeconomic developments may negatively affect a range of financial intermediaries and

markets at the same time. These different forms of systemic risk can also be interrelated. For example, contagion risk may be more pronounced in a business cycle downturn, when financial intermediaries are already weakened. This special feature reviews three recent modelling frameworks developed at the ECB which can be used to assess these different aspects of systemic risk.² The first section describes an econometric framework that is used to estimate the extent to which individual financial institutions contribute to overall systemic risk, based on stock price data. This tool therefore takes a cross-sectional perspective on the system which is in line with the first source of systemic risk mentioned above. The second section discusses how coincident and early warning indicators of simultaneous failures of financial institutions can be constructed from cross-sectional data for financial and non-financial firms, combined with macro-financial and credit risk data. The coincident and early warning indicators capture shared exposure to common shocks and imbalances that may build up gradually over time, i.e. the second and third forms of systemic risk. The third and final section derives a coincident indicator of systemic stress in the financial system that aggregates information from different segments of the overall financial system. With its focus on certain financial market segments as a whole, this composite indicator may be well suited to capturing systemic stress emanating from market-to-market contagion as well as from other sources of systemic risk as

1 See J. C. Trichet, "Systemic risk", Clare Distinguished Lecture in Economics and Public Policy, Clare College, University of Cambridge, 10 December 2009; V. Constâncio, "Macro-prudential supervision in Europe", speech at the ECB-CEPR-CFS conference on macro-prudential regulation as an approach to containing systemic risk – economic foundations, diagnostic tools and policy instruments, Frankfurt am Main, 27 September 2010; ECB, "The concept of systemic risk", *Financial Stability Review*, December 2009; and O. de Bandt, P. Hartmann and J. L. Peydró-Alcade, "Systemic risk in banking: An update", in A. Berger, P. Molyneux and J. Wilson (eds.), *Oxford Handbook of Banking*, Oxford University Press, 2009.

2 For a brief review of the latest advances in systemic risk measurement in the general literature, see ECB, "New quantitative measures of systemic risk", *Financial Stability Review*, December 2010.

soon as they have more widespread effects. However, because the composite indicator does not build on firm-level data in contrast to the two previous indicators, it provides no information as to where strains are located at the level of individual financial institutions.

MEASURING SYSTEMIC RISK CONTRIBUTION USING MULTIVARIATE REGRESSION QUANTILES

In the current debate on systemic risk, great emphasis has been placed on the question of how to measure the systemic importance of an individual financial institution. This is understandable since the failure of a systemically important financial institution could produce severe negative externalities with a bearing on the whole financial system, with the default of Lehman Brothers being a forceful case in point. It has been argued that the supervisory and regulatory treatment of such firms should take their systemic importance into account, thereby creating incentives for institutions to internalise some of these adverse externalities. For this purpose, however, financial authorities have to rely on quantifiable measures of the systemic risk created by individual financial institutions.

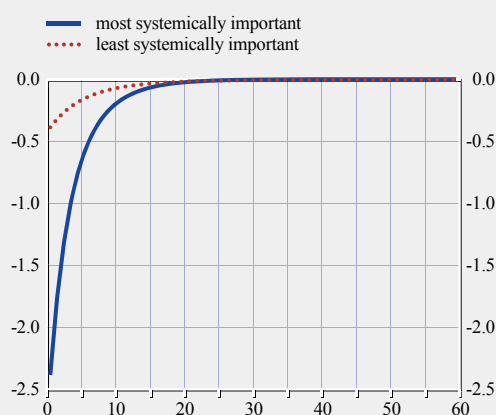
A popular means of assessing the systemic importance of a financial institution is to look at the sensitivity of its value at risk (VaR) to shocks to the whole financial system.³ White, Kim and Manganelli propose a novel method of estimating such sensitivity.⁴ The methodology is based on a vector autoregressive (VAR) model, in which the dependent variables are the VaR of individual financial institutions and of the overall market, which depend on (lagged) VaR and past shocks. The authors demonstrate the way in which the parameters of the model can be estimated using multivariate regression quantiles. Regression quantile estimates are known to be robust to extreme values. This is arguably important for the purpose of measuring systemic importance since situations of severe financial strains are rare events, and the model is intended to estimate linkages between individual financial institutions and the market as a whole under such rare circumstances. A multivariate version allows

researchers to measure directly tail dependence among the random variables of interest. By casting regression quantiles in a VAR framework, it is possible to estimate the spillover and feedback effects among the variables of the system, as well as the long-run VaR equilibria and associated impulse response functions.

Chart C.1 presents an application of this methodology. The model has been estimated on a sample of 22 large EU banks. It displays two average impulse responses. The solid line, labelled “most systemically important”, is the average impulse response of the three banks whose VaR is most affected by a shock to the stock market. The dashed line, labelled “least systemically important”, is the impulse response of the three banks whose VaR is least sensitive to a stock market shock.

- 3 See, for instance, T. Adrian and M. Brunnermeier, “CoVaR”, *Federal Reserve Bank of New York Staff Reports*, No 348, September 2008; V. V. Acharya, L. H. Pedersen, T. Philippon and M. Richardson, “Measuring Systemic Risk”, *New York University Working Paper*, 2010; and C. T. Brownlees and R. F. Engle, “Volatility, Correlation and Tails for Systemic Risk Measurement”, *New York University Working Paper*, 2010.
- 4 H. White, T.-H. Kim and S. Manganelli, “VAR for VaR: measuring systemic risk using multivariate regression”, *ECB Working Paper Series*, forthcoming.

Chart C.1 VAR for VaR impulse responses



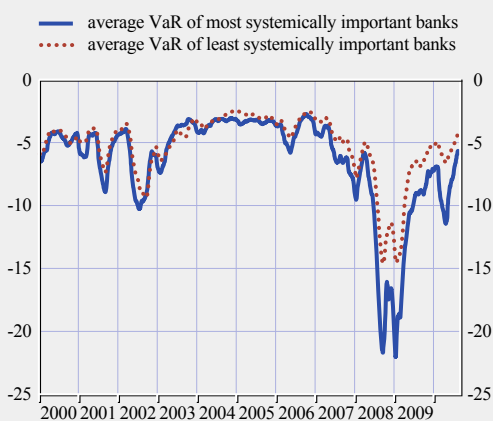
Sources: Thomson Reuters and ECB calculations.
Notes: Average VaR reaction of the most systemic and least systemic banks to a 1% stock market shock. The horizontal axis measures weeks, while the vertical axis is expressed in percentage stock price weekly returns.

There is a striking difference in behaviour between the two groups. While the least systemically important banks are barely affected by common shocks (their VaR increases by less than 0.5%), the impact on the VaR of the most systemically important banks is more than five times higher. The persistence of the shock, on the other hand, is quite comparable, as in both cases it appears to die out after the twentieth week.

As a possible way to validate and illustrate the usefulness of the model, Chart C.2 plots over time the average VaR associated with the two groups of banks. To facilitate the comparison, the data were smoothed with a 60-day moving average. The chart presents two striking facts. In normal times, i.e. before the onset of the crisis in mid-2007, the VaR of the most and least systemically important groups of banks is roughly equal. The VaR of the least systemically important banks even exceeded the VaR of the most systemically important ones during some periods in 2003. The situation changes abruptly with the beginning of the financial crisis. The VaR of the most systemically important banks increases significantly more than that of the least systemically important banks from 2008 onwards, showing a greater exposure to common shocks.

Chart C.2 VaR of most and least systemically important banks

(Jan. 2000 – Nov. 2010)



Sources: Thomson Reuters and ECB calculations.

Notes: Time evolution of the average VaR of the most and least systemically important banks. 60-day moving average.

The application illustrates how the proposed methodology can be used to identify the set of banks which may be most exposed to common shocks, especially in times of crisis. Of course, this should only be considered as a partial, model-based screening device for identifying the most systemically important banks. Further analysis, market intelligence and sound judgement are other necessary elements to produce a reliable risk assessment of large banking groups.

COINCIDENT AND EARLY WARNING INDICATORS BASED ON CREDIT RISK CONDITIONS

Credit risk from correlated exposures is a dominant source of risk for financial firms. As a result, changes in credit risk conditions matter for the profitability and solvency of financial intermediaries, and overall financial stability. Schwaab, Koopman and Lucas study how macro-financial fundamentals and credit risk conditions interact to yield clusters of financial and non-financial firm failures.⁵ After estimating the model parameters and the risk factors underlying financial distress, these factors are then combined to form coincident indicators and forward-looking indicators of common stress and the likelihood of simultaneous financial firm failures.

Conceptually, coincident measures of financial distress can be compared to thermometers that a policy-maker can plug into the financial system to read its “heat”. A straightforward indicator of such distress is the aggregate likelihood of failure for financial sector firms (banks as well as non-bank financial firms). However, such a time-varying failure rate is hard to obtain. First, financial firms rarely default. Second, risk factors other than readily available macroeconomic and financial indicators are important for quantifying financial distress. Financial firms are “special” along a number of dimensions, and additional data sources and risk factors are required to approximate their risk dynamics.

5 B. Schwaab, A. Lucas and S. J. Koopman, “Systemic risk diagnostics: coincident indicators and early warning signals”, *ECB Working Paper Series*, No 1327, April 2011.

Chart C.3 plots a model-implied failure rate for a large cross section of EU and US financial firms. The failure rate is the share of overall intermediaries that can be expected to fail over the next three months. The failure rate refers to approximately 450 US and 400 EU rated financial firms. It includes banks, insurers and real estate firms (also special-purpose vehicles and thrifts, as long as they have received a rating, but not hedge funds). As a result, the reported failure rate takes into account a significant part of the parallel banking system, i.e. non-bank financial firms that play an important role in the intermediation process.

The chart compares the model-based failure rates for a broad set of financial firms with the mean expected default probability (EDF) for the twenty largest financial firms in the United States and the EU. The distress in each region during the years 1991, 2001 and 2007-10 is visible from the chart. The financial sector failure rate is different from and almost always higher than what is suggested by an analysis of the average EDFs for the largest (and highly rated) financial firms in each region. Essentially, the model

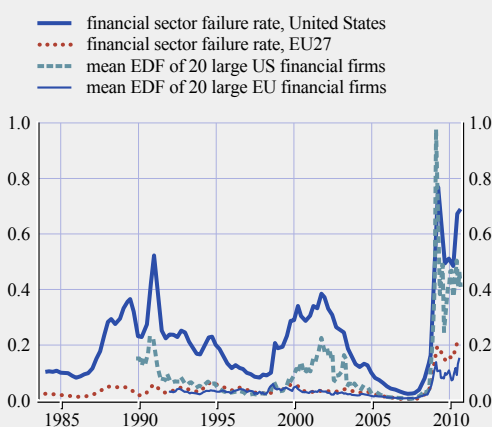
borrowes the risk dynamics as implied by the EDF data to infer the risk dynamics for the larger cross section of all rated financial firms. From the fourth quarter of 2010, both the mean EDF and the model-implied rate suggest high levels of common stress for EU financial firms.

Systemic risk is necessarily a multivariate concept, involving a system of banks and non-bank financial firms. The notion of systemic risk can be made operational as the risk of experiencing a systemic event, such as the simultaneous failure of a large number of financial institutions. Conceptually, simultaneous failures are analogous to disasters such as earthquakes and tsunamis – unlikely events for the most part, but with an asymmetrically large and potentially devastating impact if the risk materialises.

Joint failure probabilities can be inferred from the large-dimensional factor model. The model structure is chosen such that it captures the skewness and fat tails that are typical of joint failure distributions. The three-dimensional graph in Chart C.4 plots the probability of at least $k\%$ of financial firms failing over a one-

Chart C.3 Failure rates for financial firms in the EU and the United States

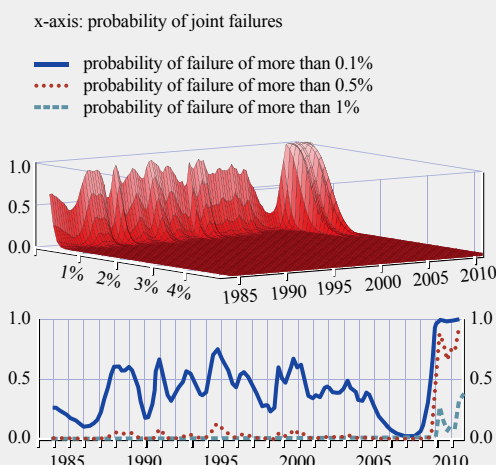
(Q1 1984 – Q4 2010)



Sources: Moody's, Moody's KMV, Thomson Reuters and ECB calculations.
Note: The horizontal axis measures time, while the vertical axis measures quarterly failure probabilities.

Chart C.4 Implied probability of simultaneous MFI failures in the EU

(Q1 1984 – Q4 2010)



Sources: Moody's, Moody's KMV, Thomson Reuters and ECB calculations.
Note: The horizontal axes measure time, while the vertical axes measure joint failure probabilities over a one-year horizon.

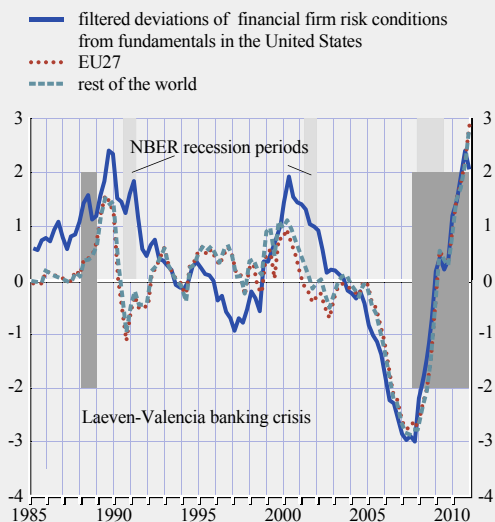
year horizon (z-axis), as a function of k (y-axis), over time from the first quarter of 1984 to the fourth quarter of 2010 (x-axis). The bottom panel cuts the three-dimensional plot into various slices along the time dimension: at 0.1%, 0.5% and 1% of overall financial sector firms. The estimates reveal that, in the fourth quarter of 2010, the probability of failure of at least 1% of financial sector firms (e.g. at least four firms of average size out of four hundred firms), at coincident levels of stress, is around 30%. As a result, there is a substantial risk of simultaneous failures. A more detailed analysis may reveal the sources of the joint risk.

Coincident risk indicators, such as current marginal and joint failure probabilities, do not provide forward-looking signals of financial distress. Recent research at the Bank for International Settlements (BIS) and the ECB on early warning indicators points towards the importance of credit market activity.⁶ In order to obtain a related but different early warning signal for future financial stability, Schwaab, Koopman and Lucas⁷ argue that in addition to tracking *credit quantities* over time (such as the private credit-to-GDP ratio), a policy-maker can also benefit from tracking *credit risk conditions* over time. Credit quantities and credit risks are related – it is harder to default if firms have easy and ample access to credit. Conversely, firms come under stress if credit is rationed.⁸

Chart C.5 plots a “credit risk deviations” early warning indicator. The indicator captures the extent to which local stress in a given industry (the financial industry in this case) differs from that suggested by macro-financial fundamentals. The figure compares estimated deviations in the United States, the EU and the rest of the world. The light and dark shaded areas correspond, respectively, to National Bureau of Economic Research (NBER) recession periods for the United States and episodes of banking crises as identified by Laeven and Valencia.⁹ Deviations larger than one in all regions may define a global warning signal. The chart demonstrates that a significant and persistent decoupling of risk conditions from fundamentals preceded in

Chart C.5 Deviations of credit risk conditions from macro fundamentals for financial firms

(Q1 1984 – Q4 2010)



Sources: Moody's, Moody's KMV, Thomson Reuters, and ECB calculations.

Note: The horizontal axis measures time, while the vertical axis measures absolute deviations of risk conditions from fundamentals.

particular the financial crisis and recession of 2007-09. In the years leading up to the crisis, risk conditions were significantly below those suggested by macro-financial fundamentals. Currently, financial firms' risk conditions are substantially higher than those suggested by current macroeconomic fundamentals. This may reflect that the fundamentals do not take into account sovereign default risk conditions.

6 C. Borio and M. Drehmann, “Assessing the risk of banking crises – revisited”, *BIS Quarterly Review*, March 2009, and L. Alessi and C. Detken, “Quasi real time early warning indicators for costly asset price boom/bust cycles: a role for global liquidity”, *European Journal of Political Economy*, 2011.

7 See footnote 5.

8 For deviations of credit risk from observed macro-financial conditions, see S. Das, D. Duffie, N. Kapadia, and L. Saita, “Common Failings: How Corporate Defaults are Correlated”, *The Journal of Finance*, Vol. 62, Issue 1, February 2007. See also S. J. Koopman, A. Lucas, and B. Schwaab, “Modeling frailty-correlated defaults using many macroeconomic covariates”, *Journal of Econometrics*, Vol. 162, Issue 2, June 2011, forthcoming.

9 L. Laeven and F. Valencia, “Resolution of Banking Crises: The Good, the Bad, and the Ugly”, *IMF Working Paper*, No 10/146, June 2010. This research suggests two banking crises in the United States (in 1988 and from 2007 onwards) and one in the EU (from 2008 onwards).

A COINCIDENT INDICATOR OF SYSTEMIC STRESS

This section presents a recent indicator of contemporaneous financial stress called the “composite indicator of systemic stress” or simply CISS (pronounced “kiss”).¹⁰ It aims to measure the current state of instability, i.e. the current level of frictions, stresses and strains (or the absence thereof) in the financial system and to condense that state of instability into a single statistic. The CISS permits not only the real-time monitoring and assessment of the stress level in the whole financial system, but may also help to delineate and characterise historical episodes of “financial crises”. Such episodes might then be better compared and studied empirically in the context of early warning signal models, for instance.¹¹ Last but not least, composite financial stress indicators can also be used to gauge the impact of policy measures directed towards mitigating systemic stress.

The CISS captures several symptoms of stress in different segments of the financial system, such as increases in agents’ uncertainty (e.g. about asset valuations or the behaviour of other investors), in investor disagreement or in information asymmetries intensifying problems of adverse selection and moral hazard (e.g. between borrowers and lenders). It also captures lower preferences for holding risky or illiquid assets (flight to quality and liquidity, respectively). The CISS measures such stress symptoms mainly by financial market indicators which are quite standard in the literature (such as volatilities, risk spreads and cumulative valuation losses). These indicators are readily available for many countries at a daily frequency in general and with relatively long data histories.

The main methodological innovation of the CISS compared with alternative financial stress indicators is the application of standard portfolio theory to the aggregation of the underlying individual stress measures into the composite indicator. For this purpose, 15 homogenised¹² individual stress measures are

first grouped into five sub-indices representing arguably the most important segments of an economy’s financial system: the bank and non-bank financial intermediaries sector; money markets; equity and bond markets; and foreign exchange markets. Each sub-index is calculated as the simple mean of the transformed values of three individual stress measures for each market segment. The five sub-indices are then aggregated on the basis of their time-varying cross-correlation structure in the same way as the overall risk of an asset portfolio is calculated from the risk characteristics of its individual assets. As a result, the CISS puts relatively more weight on situations in which stress prevails in several market segments at the same time. The second element of the aggregation scheme featuring systemic risk is the fact that the “portfolio weights” attached to each of the five sub-indices reflect to some extent their relative importance for economic activity.¹³

Chart C.6 displays the CISS calculated for the euro area as a whole.¹⁴ It clearly shows how systemic stress emerged in August 2007; how the situation escalated into a full-blown financial crisis after the bankruptcy of Lehman Brothers in September 2008; and how the sovereign debt crisis interrupted the process of relaxation from April 2010.

10 D. Hollo, M. Kremer and M. Lo Duca, “CISS – A ‘Composite Indicator of Systemic Stress’ in the Financial System”, November 2010, available at <http://www.ssrn.com>. The CISS was briefly introduced in ECB, “Analytical models and tools for the identification and assessment of systemic risk”, *Financial Stability Review*, June 2010.

11 See, for example, M. Lo Duca and T. Peltonen, “Macro-financial vulnerabilities and future financial stress: assessing systemic risks and predicting systemic events”, *ECB Working Paper Series*, No 1311, March 2011.

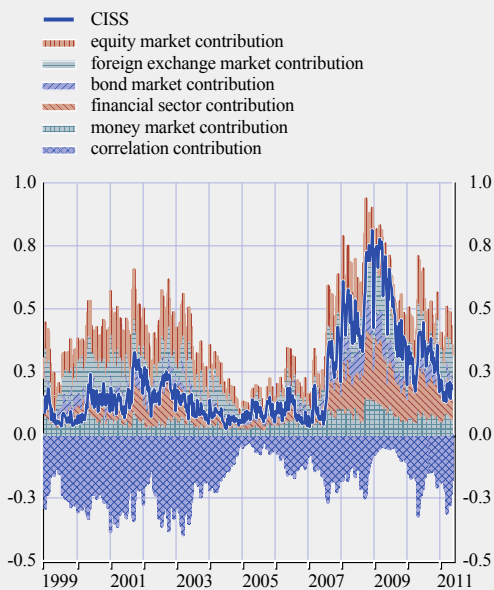
12 Before aggregation, the individual stress measures need to be harmonised on a common scale. For this purpose, each raw indicator is transformed on the basis of order statistics such that each transformed indicator measures financial stress on an ordinal scale ranging from zero to one, a property also inherited by the CISS. For details, see D. Hollo, M. Kremer and M. Lo Duca, op. cit.

13 The sub-index weights for the euro area CISS are: money market: 15%; bond market: 15%; equity market: 25%; financial intermediaries: 30%; and foreign exchange market: 15%.

14 The CISS is also available as an EU aggregate, where the euro area CISS is averaged with CISSs for the Czech Republic, Denmark, Hungary, Poland, Sweden and the United Kingdom, based on relative real GDP weights.

Chart C.6 Composite indicator of systemic stress (CISS) for the euro area

(Jan. 1999 – May 2011)



Sources: Thomson Reuters, ECB and ECB calculations.

The chart also plots the stacked plain contributions from each sub-index by ignoring their cross-correlations. The upper border of the upper area is thus equivalent to the weighted average of the five sub-indices. Such averaging implicitly assumes perfect correlation across all of the sub-indices all the time. The difference between this “simple average” CISS and the CISS proper thus reflects the impact of the cross-correlations and is plotted in the chart as the area below the zero line.

One can see that whenever financial stress is extremely high (or extremely low) in all market segments at the same time, all cross-correlations increase strongly and the CISS approaches the simple average of sub-indices. It can therefore be said that the simple average overstates the level of financial stress in normal times when correlations are relatively moderate, and introduces a bias in its information content in such circumstances. For instance, the CISS clearly identifies the current financial crisis from August 2007 as by far the most severe

period of systemic stress over the past quarter of a century.¹⁵ By contrast, the simple average of sub-indices would not be able to differentiate between the peak levels of stress caused by the dot-com bubble and bust cycle around the turn of the century (which was mainly driven by stock market stress), and during the first year of the “sub-prime” crisis (i.e. from its outbreak in August 2007 until the bankruptcy of Lehman Brothers). Since this may appear implausible with the benefit of hindsight, indicators not incorporating the systemic nature of stress could provide misleading information regarding the “true levels” of strains in the financial system as a whole.

In line with contemporaneous definitions of systemic risk, the CISS is designed to capture two crucial characteristics of systemic stress, namely that instability is widespread within the financial system (“horizontal view”) and usually very costly for an economy (“vertical view”).¹⁶ A simple way to think of the second view is that activity in the real economy becomes severely endangered if financial stress reaches a certain threshold level. Chart C.7 shows the graphical results of a parsimonious statistical exercise estimating and testing such a critical benchmark level of systemic stress. The procedure tests the hypothesis that the empirical relationship between annual growth in industrial production and the CISS (four months lagged) switches across two different regimes, where the regimes depend on whether the CISS lies above or below a certain threshold level.¹⁷ The results indeed suggest that the economy behaves very differently when the CISS reaches a level of 0.36 or above. While at lower levels of the CISS the scatter plot appears to be purely

15 The data sample of a backward extended version of the euro area CISS starts in January 1987.

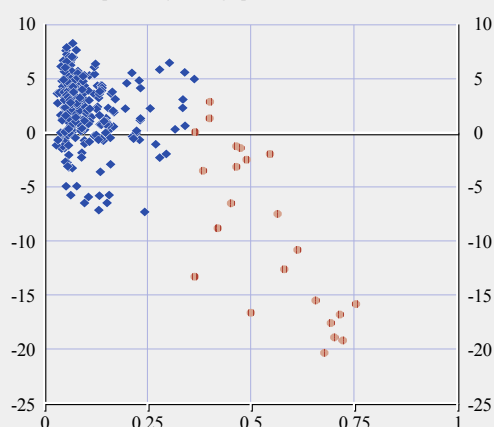
16 See ECB, “The concept of systemic risk”, *Financial Stability Review*, December 2009.

17 The procedure applies a grid search algorithm, and the preferred threshold level is the one which rejects the null hypothesis of no regime difference with the highest likelihood. See B. E. Hansen, “Sample splitting and threshold estimation”, *Econometrica*, Vol. 68, No 3, May 2000.

Chart C.7 Financial stress and economic activity in the euro area

(Sep. 1987 – Oct. 2010)

x-axis: CISS
y-axis: industrial production growth
(percentage change per annum)



Sources: Eurostat, Thomson Reuters, ECB and ECB calculations.
Notes: Financial stress is measured by the CISS. The CISS is plotted against annual growth rates in industrial production four months ahead. Red dots represent such data pairs for months in which the CISS exceeds an estimated threshold level of 0.36.

random (blue diamonds), at higher levels of the CISS a clear negative relationship emerges between industrial production and financial stress (red dots), as one can expect if financial stress becomes widespread and thus systemic.

CONCLUDING REMARKS

The recent financial crisis is an overwhelming example of systemic risk which had gradually built up to a point where the amplification and propagation of a series of relatively small shocks eventually led to widespread financial collapse and a global recession only comparable to the Great Depression. There is general agreement that in order to avoid such disasters happening again, financial authorities need to better identify, assess and control the level of systemic risk prevailing in the financial sector. But this is easier said than done because of the complexity as well as the multifaceted and elusive nature of systemic risk. In addition, the theoretical and empirical research on systemic risk is still in its early developmental stage. This, in turn, implies that financial authorities have to build

up, from scratch, a wide range of measures and tools covering different aspects of systemic risk in different parts of the financial system, with each tool having its specific purposes, advantages and caveats that must always be borne in mind when interpreting its results. This of course also applies to the three new systemic risk measurement tools presented in this special feature.