

Box 6

MEASURING SYSTEMIC RISK CONTRIBUTIONS OF EUROPEAN BANKS

A clear lesson of the global financial crisis has been the propensity for company-specific risk to spill over to other firms. In fact, it is not just a company's size and idiosyncratic risk but also its interconnectedness with other firms which determine its systemic relevance. This realisation has underpinned not only a growing set of tools to capture such systemic risk, but also numerous regulatory initiatives to limit and mitigate it.

Of the multiple methodologies which have gained prominence to date in capturing systemic risk contributions of individual institutions, few have touched upon the time-varying nature of this process. This box illustrates a novel methodology that builds on the concept of value at risk (VaR) and can explicitly account for the time-varying interconnectedness within the banking sector. For each bank, the underlying statistical approach identifies the relevant tail-risk drivers as the minimum set of macro-financial fundamentals, firm-specific characteristics and risk spillovers from other banks driving its VaR. Detecting with whom and how strongly any institution is connected allows the estimation and construction of a tail-risk network of the financial system. A bank's contribution to systemic risk is then defined as the effect of an increase in its individual tail risk on the VaR of the entire system, conditional on the bank's position within the financial network as well as overall macro-financial conditions. The analysis¹ is based on publicly available market and balance sheet data and is applied to a sample of 51 large European banks.

The proposed concept is related to the widely used systemic risk measure of CoVaR.² However, the methodology outlined in this box does not constrain time variation in systemic risk to variation in idiosyncratic risk. More importantly, neither CoVaR nor alternative approaches to quantifying systemic risk contributions, such as marginal expected shortfall or distressed insurance premia, explicitly consider network interconnections, which are key determinants of banks' systemic risk contributions.³ Such approaches cannot detect spillover effects driven by the topology of the risk network and thus might underestimate the systemic importance of smaller but very interconnected banks.

The empirical implementation of the statistical model is based on a two-stage quantile regression. In the first step, bank-specific VaRs are estimated as functions of firm characteristics, macro-financial state variables as well as tail-risk spillovers of other banks. Hereby, the major challenge is to shrink the high-dimensional set of possible cross-linkages among all banks to a feasible number of relevant risk connections. Novel Least Absolute Shrinkage and Selection Operator (LASSO) techniques⁴ address this issue and allow the identification of the relevant tail-risk drivers for each bank in a fully automatic way. The resulting tail dependence network can be represented in terms of a network graph as illustrated in Chart A, which shows some indications of fragmentation of the European interbank market, as the banks in the programme countries are estimated to be disconnected from the other European banks. Moreover, during the European sovereign debt crisis, the tight interconnections between banks and sovereigns have played an important role. To account for this, sovereign bond yields are modelled (under an alternative

1 The analysis is based on F. Betz, N. Hautsch, T. Peltonen and M. Schienle, "Measuring systemic risk contributions of European banks", *ECB Working Paper Series*, forthcoming – building on N. Hautsch, J. Schaumburg and M. Schienle, "Financial Network Systemic Risk Contributions", SFB 649 Discussion Paper 2012-053, available at <http://sfb649.wiwi.hu-berlin.de/papers/pdf/SFB649DP2012-053.pdf>, 2012.

2 T. Adrian and M. Brunnermeier, "CoVaR", *Federal Reserve Bank of New York Staff Reports*, No 348, September 2011.

3 ECB, "Analytical models and tools for the identification and assessment of systemic risk", *Financial Stability Review*, June 2010.

4 A. Belloni and V. Chernozhukov, "l1-penalized quantile regression in high-dimensional sparse models", *Annals of Statistics*, Vol. 39, No 1, pp. 82-130, 2011.