Box 6
The information in systemic risk rankings

One of the legacies of the 2008-09 global financial crisis has been a proliferation of approaches to quantifying and ranking the contributions of firms in the financial sector to "systemic risk". Risk rankings can be based on a variety of well-known systemic risk measures, such as "SRISK" or "Delta CoVaR", or, alternatively, on balance sheet items (such as a firm's leverage ratio).[47] However, these systemic risk ranking approaches have seen limited use by policy institutions such as central banks and supervisory authorities. Possible reasons for this include limited theoretical foundations and the reliance of some measures on volatile financial market data.

To evaluate the policy usefulness of such systemic risk ranking approaches, a principal components-based methodology is used to combine the systemic risk rankings of financial institutions in order to determine a robust combined ranking.[48] The combined ranking is derived from six individual rankings based on a firm's SRISK, marginal expected shortfall, leverage, systematic risk, Delta CoVaR, and value at risk, and disentangles their common (signal) and idiosyncratic (noise) components. This approach takes into account the fact that policy-makers are conscious of modelling risks and prefer to implement policies only when complementary approaches point in the same direction. The methodology was applied to the EU financial sector and covered 113 firms over 139 months, from March 2002 to September 2013.

First, combining currently available systemic risk rankings suggests that there is scope for amplifying the signal from this class of indicators, and reducing the noise attributable to modelling risk and estimation uncertainty. Indeed, there is substantial evidence that the cross-sectional consistency between different systemic risk ranking methodologies is far from perfect. Chart A presents cross-sectional scatter diagrams showing SRISK and three other rankings for a specific

47 See Brownlees, C. and Engle, R., "SRisk: A conditional capital shortfall index for systemic risk measurement", unpublished working paper, 2015, and Adrian, T. and Brunnermeier, M., "CoVaR", *Federal Reserve Bank of New York Staff Reports*, No 348, 2014. SRISK is available at http://vlab.stern.nyu.edu/. Statistics based on Delta CoVaR measures are reported in the ESRB risk dashboard; see www.esrb.europa.eu/.

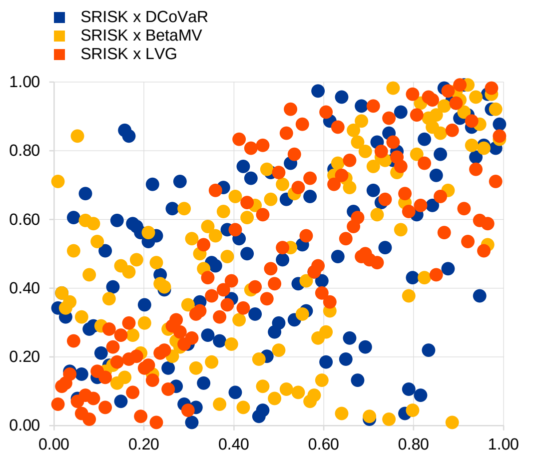
48 See Nucera, F., Schwaab, B., Koopman, S. J. and Lucas, A., "The information in systemic risk rankings", *Working Paper Series*, ECB, forthcoming, 2015. See also Tinbergen Institute Discussion Paper No 15-070.

date. The R-squared statistics from a linear regression of one ranking on another are typically low and do not exceed 0.22 in two cases (SRISK vs. Delta CoVaR, and SRISK vs. systematic risk). The association between SRISK and leverage is higher, as the latter is used in the computation of the former, but the R-squared from a linear regression does not exceed 0.66. The low association is not due to a few outliers, but is symptomatic of the different rankings ordering the firms in the sample differently. This may be problematic for supervisory purposes.

Chart A

The cross-sectional consistency between different rankings is far from perfect

Scatterplots for SRISK x DCoVaR, Beta and leverage

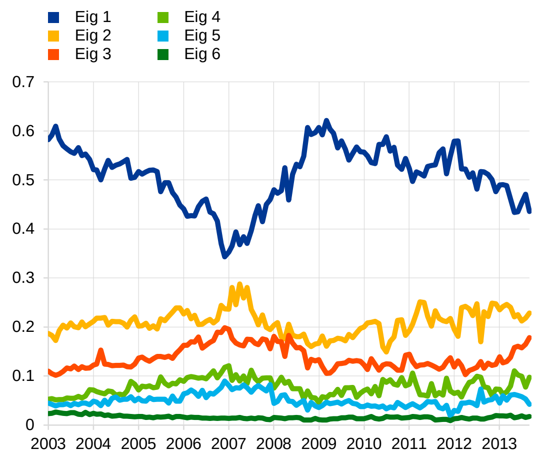


Sources: www.vlab.stern.nyu.edu and ESRB submissions.
Notes: Three scatterplots report SRISK vs. Delta CoVaR, SRISK vs. Beta x equity market capitalisation, and SRISK vs. leverage. Ranks are distributed uniformly between 0 and 1 by construction, with the most systemically important financial firm close to 1. The R-squared statistics are 0.20, 0.22, and 0.66 respectively. The rankings are reported for a specific date: 29 June 2012.

Chart B

Systemic risk rankings agree the least when they are arguably the most important

Eigenvalues from a principal components analysis



Sources: www.vlab.stern.nyu.edu and ESRB submissions.
Notes: Eigenvalues from a repeated cross-sectional factor analysis of six systemic risk rankings. Factor analysis is a statistical method used to describe the variability among observed correlated variables in terms of a potentially lower number of unobserved variables called factors. The first eigenvalue is the share of total variation in the cross-section that can be attributed to the first factor, which explains the most variation in the panel subject to a normalisation constraint. The lowest value is achieved in December 2006.

Second, the robustness of the signal from a combined ranking appears to be limited for policy purposes such as targeted banking supervision. When studying the time-series dimension of the results of the principal components analysis, an increasing discrepancy becomes apparent during 2006-07, namely between the loadings of price-based systemic risk rankings (such as value at risk, Delta CoVaR and marginal expected shortfall) versus systemic risk rankings that also incorporate book values (such as leverage and SRISK). Chart B plots the explained variances associated with the principal components across rankings over time. The explained variances appear to signal a dislocation between market prices and fundamentals prior to the onset of the 2008 financial crisis. For example, the minimal eigenvalue associated with the first principal component is obtained in December 2006. This is interesting from an early warning perspective.[49] On the other hand, this finding also suggests that different systemic risk measures signal different messages at a time when they are, arguably, the most important. This data feature is problematic from a supervisory perspective.

[49] This finding is also in line with the financial stability paradox as formulated in Borio, C., “Rediscovering the macroeconomic roots of financial stability policy: journey, challenges and a way forward”, *Working Paper Series*, No 354, BIS, 2011, pp. 1-34. It is also in line with the volatility paradox as formulated in Brunnermeier, M. and Sannikov, Y., “A macroeconomic model with a financial sector”, *American Economic Review*, Vol. 104, No 2, 2013, pp. 379-421.

Third, a robust measure of systemic risk contribution correlates negatively with financial institutions' cost of debt finance in a way that is, in some cases, in line with a public sector guarantee for the most systemically important institutions. Systemic importance, when robustly measured as a weighted average across different ranking methodologies, varies inversely with a bank's credit default swap spread, provided that the respective European sovereign is financially healthy. As a result, the extent of systemic importance is associated with a benefit from a funding perspective in the market for unsecured funds.[50]

To conclude, the results summarised in this box suggest that both macroprudential and microprudential supervisors could benefit from increased attention to systemic risk rankings, as recently proposed in the academic literature. That said, such measures are subject to caveats[51], which may limit their general usefulness in terms of concrete applicability in specific circumstances. Indeed, the results support the notion that inference is most reliable if it is based on a combination of alternative approaches.

50 This is in line with the proposition in Kelly, B. T., Lustig, H. and van Nieuwerburgh, S., "Too-systemic-to-fail: what option markets imply about sector-wide government guarantees", *Working Paper Series*, No 17149, NBER, 2011. For more details on this point, see Nucera et al., ibid.

51 See, for example, Löffler, G. and Raupach, P., "Pitfalls in the use of systemic risk measures", *University of Ulm Working Papers*, 2015.