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"When Unity Makes Strength: A Systemic Risk Index"

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Background

Due to the recent financial crisis, several systemic risk measures have been proposed in the literature for quantifying financial system wide distress. In this article, we propose an aggregated Index for financial systemic risk measurement based on PCA and ICA methodologies on the several systemic risk measures released in the recent literature. We use this index to further identify the states of the market as suggested in Kouontchou *et al.* [2013]. We show, by characterizing market conditions with a Robust Kohonen Self-Organizing Maps algorithm that this measure is directly linked to crises market states and that there is a strong link between return and systemic risk.

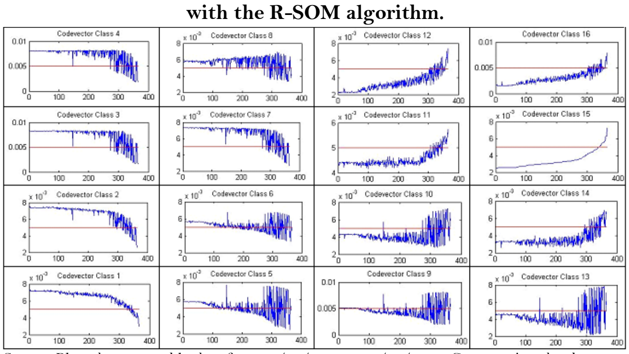
What is it about?

- Following the intuition of Giglio *et al.* [2013], we aim to create an aggregated index able to identify the main systemic risk factors through the study of the time series of 16 systemic risk measures applied to American securities. Then, we will apply a PCA and, alternatively, an ICA, on the most prominent systemic risk measures, which will allow us to build an index based on the so-called Empirical Orthogonal Functions (or independent components) and their respective weights. We try to identify the link between the proposed aggregated systemic risk index and the market states defined by a neural network classification algorithm.

R-SOM Algorithm and American Stocks

- The classification by robust Kohonen maps aims to identify the correlation between the Systemic Risk Measures and the shape of the financial market.
- We analyze a data set composed of 95 American financial institutions. Using 1-year rolling windows, each institution is measured by 6 systemic risk measures (VaR, CoVaR, MES, ΔCoVaR, SRISK, CES) at the individual firm level. Then, using the time series of these measures, we make use of the R-SOM algorithm in order to construct our classification map.

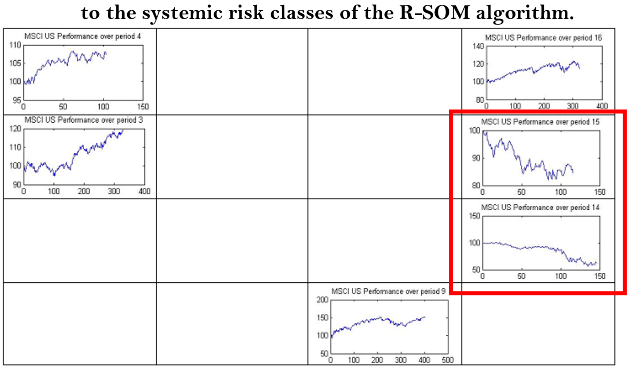
Figure 1. Codevectors of the systemic risk classes obtained with the R-SOM algorithm.



Source: Bloomberg, monthly data from 02/03/2004 to 01/06/2014. Computations by the authors.

- Figure 1 shows the codevectors of the [4x4] classes of the R-SOM algorithm, and the average value (red line) of each class in order to compare the values of these codevectors. Each class represents different dates for systemic risk measures of financial institutions. In Figure 2, we compute the performance of the MSCI US Index on the periods corresponding to the different systemic risk classes obtained with the R-SOM algorithm.

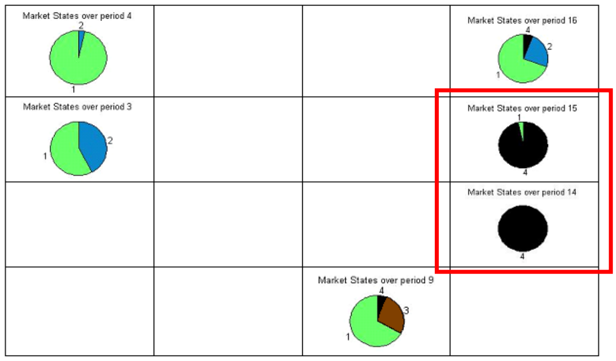
Figure 2. MSCI US performance over the periods corresponding to the systemic risk classes of the R-SOM algorithm.



Source: Bloomberg, monthly data from 02/03/2004 to 01/06/2014. Computations by the authors. Inside the red box we observe classes that represent crisis periods.

- The comparison of Figures 1 and 2 underlines the link between the systemic risk measures and the evolution of the MSCI US Index: a fall of the Index is generally associated with a positive slope in the code vectors resulting from the R-SOM of systemic risk measures.
- Figure 3 presents the proportion of dates on each class associated with each Market State as defined in Kouontchou *et al.* [2013].

Figure 3. Market states over the periods associated with the systemic risk classes



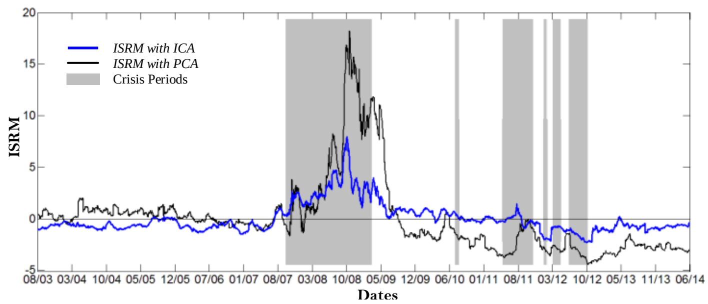
Source: Bloomberg, monthly data from 02/03/2004 to 01/06/2014. Computations by the authors. Inside the red box we observe classes belonging to market state 4 (crises).

- In Figure 3, we clearly note that classes inside the red box are exclusively composed of samples where dates are associated with market state 4 (crisis periods).

An Index of Systemic Risk Measures

- We construct an aggregated Index of Systemic Risk Measures (ISRM) based on PCA and ICA methodologies performed on 16 systemic risk measures.
- Figure 4 displays the signals corresponding to the proposed index (obtained with the two methodologies). The grey areas in the figure represent the Market Crises (market state 4).

Figure 4. Index of Systemic Risk Measures (ISRM) and crisis periods



Source: Bloomberg, daily data from 28/08/2003 to 24/06/2014. Computations by the authors.

- Figure 4 shows that long term crisis market states and the ISRM are correlated. For instance, during the crisis episode that runs from September 2007 to March 2009, we observe a high increase in the ISRM. For small crisis periods (couple of months) the ISRM does not seem to react significantly.

Relevant Literature

- KOUONTCHOU P., LENDASSE A., MICHE Y. and MAILLET B. [2013] "Forecasting Financial Markets with Classified Tactical Signals", 6 pages – *Proceedings of the European Symposium on Artificial Neural Networks 2013.*
- GIGLIO S., KELLY B. and PRUITT S. [2013], "Systemic Risk and the Macroeconomy: An Empirical Evaluation", Chicago Booth Paper n°12-49, 60 pages.

Concluding Remarks

We have been able to build a Systemic Risk Index based on mathematical algorithms relying on the variance and higher order moments between sixteen different measures, which ties in the evolution of the financial market. This has been confirmed by the simultaneity between the significant rise of our Index and long term crisis periods defined by the R-SOM algorithm.

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More information about Systemic Risk in: www.systemic-risk-hub.org