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Systemic risk in the US: Interconnectedness as a circuit breaker

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ABSTRACT

We measure systemic risk via the interconnections between the risks facing both financial and real economy firms. SIFIs are ranked by building on the Google PageRank algorithm for finding closest connections. For a panel of over 500 US firms over 2003–2011 we find evidence that intervention programs (such as TARP) act as circuit breakers in crisis propagation. The curve formed by the plot of firm average systemic risk against its variability clearly separates financial firms into three groups: (i) the consistently systemically risky (ii) those displaying the potential to become risky and (iii) those of little concern for macro-prudential regulators.

1. Introduction

The interconnections between the financial sector and the real economy mean that systemic risk can significantly affect employment and output, as strikingly illustrated by the Great Depression of the 1930s, and the weak recovery of the US economy following the collapse of Lehman Brothers and the rescue of AIG in September 2008. Surprisingly, very few empirical models of systemic risk explore the interactions between financial and non-financial firms. The empirical literature focuses on systemic risk within the financial sector itself, and in particular within the banking sector, sometimes with controls for macroeconomic or industry environment, as in [Kapadia et al. \(2012\)](#) and [Schwaab et al. \(2011\)](#), and sometimes with reference to sovereign debt, as in [Kalbaska and Gatkowskib \(2012\)](#). A survey of the extant empirical approaches is provided in [Bisias et al. \(2012\)](#).

We provide a framework for a systemic risk index based on the interconnectedness of firms from all sectors of the economy. We fill the gap in the empirical literature by explicitly recognizing the role of the real economy in initiating, amplifying and dampening systemic risk in the financial sector. Although theoretical frameworks such as [Acemoglu et al. \(2015\)](#) place the source shocks for systemic risk with the investments

of banks in real economy firms the empirical literature does not reflect this. Connectedness is fundamental to systemic risk as it lies at the heart of the transmission of shocks around the economy, and is implicit in many of the alternative definitions of systemic risk, such as the role of common shocks, firm characteristics, networks, and the impediment to the functioning of the financial markets; see for example [Allen et al. \(2012\)](#), [Huang et al. \(2012\)](#), [Drehmann and Tarashev \(2011\)](#), [Billio et al. \(2012\)](#), [Gai and Kapadia \(2010\)](#), and [Tarashev et al. \(2010\)](#).

Measuring interconnectedness is empirically challenging in these relatively large systems. Recent advances by [Diebold and Yilmaz \(2014\)](#) and [Langfield et al. \(2013\)](#) provide options for measuring both the degree and the direction of the connections in large systems. Our approach relies firstly on understanding systemic risk as interconnections in a system of time varying risk shocks, and secondly on exploiting the technology of interconnectedness algorithms, such as typified by Google search engines. In this way we produce not only an overall dynamic index of systemic risk, denoted the general systemic (GS) index, but also a means of obtaining an up-to-date ranking, known as the systemic risk (SR) ranking.

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Our ranking of individual firms in the economy captures both the cross-sectional and time dimensions of systemic risk; see also [Borio \(2003\)](#) and 2011. In the taxonomy of [Bisias et al. \(2012\)](#) this relates to cross-sectional measures examining co-dependence; including the expected capital loss or capital shortfall approach of [Acharya et al. \(2010\)](#), [Moore and Zhou \(2012\)](#), and [Brownlees and Engle \(2017\)](#). It also directly connects with the CoVar analysis of [Adrian and Brunneimeier \(2016\)](#), with an additional term relating correlation and volatility; see [Archarya et al. \(2012\)](#) and [Benoit et al. \(2013\)](#) who derive these measures in a common framework. [van de Leur et al. \(2017\)](#) recently compared our ranking system with that of simple pairwise correlations and confirmed that there is an extra degree of information available in our approach over methods such as *SRISK*, CoVAR and Marginal Expected Shortfall (see [Acharya et al. \(2010\)](#), [Adrian and Brunneimeier \(2016\)](#), [Brownlees and Engle \(2017\)](#)).

We examine the connections between shocks in risks over 500 US companies drawn from the S&P500 index for the period 2003–2011. The shocks to each company are computed from daily realized volatilities which are calculated from high frequency market trading data. Our focus on volatility as the source of risk shocks and the use of high frequency data is consistent with the approach of [Diebold and Yilmaz \(2014\)](#) who consider a system of 13 US financial institutions with daily realized volatilities; see also [Huang et al. \(2009\)](#). As [Diebold and Yilmaz \(2014\)](#) emphasize, realized volatility measures have the advantages of representing changes in market fear, and provide an indicator which increases with crisis conditions.¹

The important advantages of using market data are their timeliness and extensive coverage of a wide variety of firms in the economy. They particularly facilitate frequent updating of our proposed *GS* index for the financial sector and the *SR* ranking for each firm increasing our ability to monitor risk in the financial sector. Alternative approaches include CDS data as in [Giglio \(2011\)](#), [Markose et al. \(2012\)](#), [Nijskens and Wagner \(2011\)](#), although scope is more limited and liquidity can be problematic; [CPSS and IOSCO \(2013\)](#). Interbank lending exposure data such as used in [Langfield et al. \(2013\)](#) and interbank money market trading as in [Gratis et al. \(2016\)](#) are difficult to obtain and do not venture beyond the banking system itself. Other information such as the firm-specific metrics calculated by the [Basel Committee on Banking Supervision \(2011, 2013\)](#) to identify global systemically important banks are updated infrequently based on annual reports. Table 5 in [Bisias et al. \(2012\)](#) overviews the data inputs for 31 different systemic risk measures, emphasizing the wide range of macro and financial market data in use, and the difficulties of accessing commercially sensitive and private information.

Our empirical investigation highlights three main results. First, the index of systemic risk *GS* shows a discernible increase in the years leading up to September 2008. The index peaks in the lead-up to the Lehman Brothers bankruptcy and remains high in the following week with the accompanying uncertainty about potential rescue of other major banks and *AIG*. The index of systemic risk drops abruptly after the *AIG* rescue and the announcement and ratification of the TARP program. It increases again in April 2010 signaling the spillover effects of the European sovereign debt crisis.

Second, we compare our *GS* index with the index of [Brownlees and Engle \(2017\)](#), which is based on potential capital shortfall. Both measures indicated growing systemic risk in the lead up to September 2008. However, following the policy intervention of TARP interconnected-

¹ Earlier versions of our measure also contained three firm characteristics: leverage, liquidity and size, each which has been associated with increased probability of identifying a systemically risky firm; see [Moore and Zhou \(2012\)](#), and [Brownlees and Engle \(2017\)](#) However, we found that these had no meaningful effect on the rankings of firms using this approach, and served only to add complexity in determining the weights each characteristic should take.

ness risk falls, but systemic risk measured by capital shortfall does not, meaning that policies of this nature can act as a circuit breaker in agitating the crisis effects via the real economy; see also evidence in [King \(2011\)](#).

Third, a plot of the average systemic risk against its variability (for each firm) effectively separates three groups of financial firms and highlights two areas of considerable regulatory interest. The first consists of firms which are consistently ranked amongst the most risky in the economy and rarely move outside of this range – including *JP Morgan*, *Wells Fargo*, *Bank of America* and *Lehman* (before its demise). The second category of interest is firms with an average systemic ranking somewhere in the middle of our sample but with high variability, including *AIG*, *KeyCorp*, and *Regions Financial Corp* in our sample. These are firms which on average do not seem to be a source of concern, but which have the capacity to quickly become a problem. Financial firms are predominantly found in these two groups, providing strong evidence of the important role that macro prudential regulation may play in ensuring financial and economic stability. The final group is firms which are consistently display little systemic risk.

The paper proceeds as follows: Section 2 explains our construction of the *SR* ranking and the *GS* systemic index of the financial sector as a whole. Results are discussed in Section 3. We analyze the systemic risk index for the financial sector, and we compare it with the systemic risk index based on capital shortfall of [Brownlees and Engle \(2017\)](#). We then move to the ranking of individual firms in Section 4 and show how the plot of the average versus standard deviation of our systemic ranking for individual firms effectively contributes to the discussion on macro prudential regulation by identifying groups of firms of interest to regulatory authorities. Section 6 concludes.

2. Methodology

We use an enhanced and adapted version of the eigenvector centrality measures often used in network analysis, in particular PageRank of Google.² In a nutshell, we consider a network of financial and non-financial firms. Each firm is endowed with a level of risk, reflecting a potential for default. In line with previous literature ([Acemoglu et al., 2015](#), and references therein), we consider the shocks in these risks. The connections between the firms are represented by the correlations between the shocks. A firm is systemically important if its shock is connected to many other financial and non-financial shocks, and if its strongest linkages are with other companies that are also systemically important.

Let N be the number of firms in the system; both financial and non financial. We denote by S_{kt} the systemic importance, or centrality, of firm k at time t . It depends on the systemic importance of its peers:

$$S_{kt} = \sum_{j=1}^N S_{jt} c_{kjt}. \quad (1)$$

The time varying c_{kjt} represents the transmission channel between companies k and j at time t . The shocks in risk are computed by filtering the daily realized volatilities with ARFIMA models (as will be explained in Section 3). The dynamics of the network are given by the strength of the connections, which is captured by the correlations between shocks in risk, denoted by ρ :

$$c_{kjt} = \frac{|\rho_{kjt}|}{\sum_{i \in S_{jt}} |\rho_{ijt}|}. \quad (2)$$

² As originally proposed in [Brin and Page \(1998\)](#).

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