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Googling SIFIs

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Googling SIFIs

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Abstract

To measure the systemic risk in financial markets, and rank systemically important financial institutions (SIFIs), we propose a methodology based on the Google PageRank algorithm. We understand the economic system as interconnected risk shocks of firms in both the financial sector and the real economy. By taking into account both sectors, we demonstrate the efficacy of intervention programs, such as the TARP, as circuit breakers in the propagation of crises – something not evident in applications which address only financial firms.

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JEL classification: G01, G21, E02, G28

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1 Introduction

Macro prudential regulation is motivated by the specter of systemic risk – that is, the possibility of a financial system collapse arising from the weakness of one firm or an unanticipated external shock. 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 explores the interactions between financial and non-financial firms. The 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). A survey of the extant empirical approaches is provided in Bisias et al. (2012).

This paper provides a framework for a systemic risk index based on the interconnectedness of firms from all sectors of the economy. Connectedness is fundamental to systemic risk as it lies at the heart of the transmission of shocks around the economy, whether they are expected or not. Connectedness is also implicit in many of the alternative definitions of systemic risk, such as the role of common shocks, of firm characteristics such as size or leverage, networks, or general impediment to the functioning of the financial markets; see for example Allen et al. (2010), Huang et al. (2011), Drehmann and Tarashev (2011), Billio et al. (2012), Gai and Kapadia (2010), Darolles et al. (2012), and Tarashev et al. (2010).

Measuring interconnectedness is empirically challenging in these relatively large systems. Recent advances by Diebold and Yilmaz (2013) 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, the SIFIRank, for every systemically important financial institution (SIFI) included.

The dynamic and large dimensional system aspects of the approach captures both the cross-sectional and time dimensions of systemic risk; see also Schwaab et al. (2011). In the taxonomy of Bisias et al. (2012) this relates to cross-sectional measures examining co-dependence. These include the expected capital loss or capital shortfall approach of Acharya et al. (2010), Moore and Zhou (2012) and Brownlees and Engle (2011). The latter can be shown to directly relate to the CoVar analysis of Adrian and Brunnemeier (2011) with an additional term relating correlation and volatility; see Archarya et al. (2012); see also Benoit et al. (2013) who derive these measures in a common framework.

We examine the connections between over 500 US companies drawn from the S&P500 index for the period 2003-2011. The risk shocks to each company are modeled with daily realized volatilities calculated from high frequency market trading data, and augmented by firm characteristics of leverage, liquidity and size. 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 (2013) who consider a system of 13 US financial institutions with daily realized volatilities; see also Huang et al. (2009). As Diebold and Yilmaz (2013) emphasize, realized volatility measures have the advantages of representing changes in market fear, and provide an indicator which increases with crisis conditions. The three firm characteristics included in our measure – leverage, liquidity and size – have each been associated with increased probability of identifying a systemically risky firm; see Moore and Zhou (2012), and Brownlees and Engle (2011).

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, such as in the GS index for the financial sector and SIFIRank proposed here. CDS data are an alternative available for some institutions, such as in Giglio (2011), Markose et al. (2010) and Nijskens and Wagner (2008). Other measures such as interbank lending exposure data used in Langfield et al. (2013) are difficult to obtain frequently and do not venture beyond the banking system itself. The firm-specific metrics calculated by the Basel Committee on Banking Supervision (2011, 2013) to identify global systemically important banks are expected to be updated every three years 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.

There are five main findings in this paper. 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, the inclusion of real sector firms highlights the potential importance of these linkages for policy actions. When real economy linkages are excluded from our measure, the reduction in systemic risk associated with policies such as TARP is substantially lessened. As these policies affected the whole financial sector, they did not result in as much reduction in connections within the financial sector as they did weaken the transmission between the financial sector and the real economy. In this sense, policies of this nature can act as a circuit breaker in agitating the crisis effects; see also evidence in King (2011).

Third, we apply the bucketing approach of the Basel Committee on Banking Supervision (2011, 2013) to our SIFIRank to assign systemic importance into four buckets representing increasing levels of additional loss absorbency requirements. Four banks are consistently in the top 10 most systemically important financial firms throughout the sample: Bank of America, JP Morgan, Goldman Sachs and Wells Fargo. Citigroup and Lehman Brothers comprise a further two of the top 10 in the period prior to 2008, and after the crisis nadir, Bank of New York Mellon and American Express. Insurers, such as Prudential and Metlife, appear in the top 10 at the end of 2011.

Fourth, we compare SIFIRank with the ranking of SRISK by Acharya et al. (2010), an alternative for detecting changes in the systemic riskiness of individual firms, facilitated by the consistently updated V–Lab project at Stern School of Business. Benoit et al. (2013) show that this measure is highly correlated with leverage. A direct comparison of the results from our SIFIRank with the SRISK shows important differences. While both measures indicated growing systemic risk for a number of key firms in the lead up to September 2008, the policy interventions of TARP and the AIG rescue calmed the concerns of transmission via interconnectedness, while SRISK measures remained high. A clear result from the comparison is that at times the SRISK ranking is quite volatile – to an extent that seems to limit its usefulness for macro prudential policy regulators. This is not the case for our SIFIRank.

Last, we find it convenient to plot average systemic risk against the variance of this measure for each firm to form a curve we denote the *boomerang* curve as a consequence of its shape. The curve highlights two areas of considerable regulatory interest. The first consists of firms which are consistently ranked amongst the most risky 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 variance, including in our sample AIG, KeyCorp, and Regions Financial Corp. 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 paper proceeds as follows: Section 2 provides a more detailed discussion of the definition of systemic risk adopted in this paper. Section 3 explains our construction of the SIFIRank and the GS systemic index of the financial sector as a whole. Section 4 provides details on the new data set constructed for this paper. Results are discussed in Section 5. We analyze the systemic risk indices for the financial sector, including a study of the importance of the linkages to real economy firms. We then move to the ranking of individual firms, and finally we focus on a selection of firms, some of which played a crucial role in the development of the crisis. Section 6 concludes.

2 Dissecting the definitions of systemic risk

Although there is no universally accepted definition of systemic risk, a number of important elements are common to the definitions emerging from the European Central Bank, the Financial Stability Board, and academic work such as He and Krisnamurthy (2012). Trichet (2009) identified the problem as the

> *threat that developments in the financial system can cause a seizing–up or breakdown of this system and trigger massive damages to the real economy.*

The Financial Stability Board (2011) identified systemically important financial institutions as those

> *whose distress or disorderly failure, because of their size, complexity and systemic interconnectedness, would cause significant disruption to the wider financial system and economic activity.*

Finally, He and Krisnamurthy (2012) refer to the case where

> *shocks lead to states where a disruption in financial intermediation adversely affects the economy and feeds back into further disrupting financial intermediation.*

There are four essential elements common to these definitions which form the basis of our modelling framework.

A system of risks We understand the morphological meaning of systemic risk as a system of risks, or measuring how risks among firms in the economy are connected via their transmission channels.

Risk shocks A crucial component of systemic risk is that it threatens the financial system. A threat is an expression of potential to inflict damage, meaning that it may or may not happen. It has therefore an unexpected – or shock – sense. The object of interest therefore is the system of shocks in risks rather than of risks themselves.

The financial sector and the real economy Trichet (2009), the Financial Stability Board (2011) and He and Krisnamurthy (2012) particularly acknowledge that threats in the financial sector may severely impact the real economy, as the two are intertwined. Indeed, the core businesses of the financial industry are taking deposits and lending to the real economy, and insuring it. Since a shock in the financial sector may trigger a crisis in the rest of the economy, the focus of the analysis is the relations between shocks in risks not only within financial firms but also between the financial and non-financial sectors. Importantly, He and Krisnamurthy (2012) also refer to the potential for a feedback cycle between the financial and real economy sectors.

Common and idiosyncratic shocks It is well-established in the literature that there may be common or idiosyncratic triggers to potentially systemic crisis events. Exemplars include the float of the Thai bhat in 1997 as an idiosyncratic shock to Asian financial markets prompting the East Asian crisis, and the credit crunch in 2007-08 as a common shock affecting European and US banks.[1]

These four features of systemic risk are represented in our modelling framework as follows: Consider a dynamic and weighted network of N firms, in which $x_{j\,t}$ represents the risk for asset j $(j = 1, ..., J)$ at time t $(t = 1, ..., T)$. We are interested in the connections between the shocks to these assets, denoted by $v_{j\,t}$. To extract the shocks, we represent the evolution of $x_{j\,t}$ as a dynamic filter: $x_{j\,t} = C_j(L)v_{j\,t}$. This filter has the useful properties that by inverting the lag polynomial the shocks are easily computed, and that, conditional on information up to $t-1$, the covariance between risks and between shocks is the same: $Cov(x_{j\,t}, x_{k\,t}|\mathcal{I}_{t-1}) = Cov(v_{j\,t}, v_{k\,t}|\mathcal{I}_{t-1})$. The strength of the connection between the shocks is given by the conditional correlations $\rho_{j\,k\,t} = Corr(v_{j\,t}, v_{k\,t}|\mathcal{I}_{t-1})$.

This modeling framework easily accommodates the presence of both common and idiosyncratic shocks in the system. Let u_t and $\varepsilon_{j\,t}$ be the common and idiosyncratic shocks

[1] A common framework and empirical treatment of common and idiosyncratic shocks may be found in Dungey and Martin (2007) and Dungey et al. (2011)

respectively. Then $x_{j\,t}$ admits a factor representation:

$$x_{j\,t} = \lambda_j A_j(L) u_t + B_j(L)\varepsilon_{j\,t}.$$

Multiplying both sides by $C_j(L)^{-1}$, and recalling that $v_{j\,t} = C_j(L)^{-1}x_{j\,t}$, results in an expression for the risk shocks in terms of the common and idiosyncratic shocks

$$v_{j\,t} = \lambda_j C_j(L)^{-1} A_j(L) u_t + C_j(L)^{-1} B_j(L)\varepsilon_{j\,t}.$$

The covariance between risk shocks, conditional on information up to $t-1$, is:

$$Cov(v_{j\,t}, v_{k\,t}|\mathcal{I}_{t-1}) = \lambda_j \lambda_k Var(u_t|\mathcal{I}_{t-1}) + Cov(\varepsilon_{j\,t}, \varepsilon_{k\,t}|\mathcal{I}_{t-1}).$$

The higher the covariance between idiosyncratic shocks ($\varepsilon_{j\,t}$ and $\varepsilon_{k\,t}$) and/or the volatility of common shocks (i.e. the variance of u_t), the higher the interconnection between the risk shocks of firms j and k.

In the next section we introduce an index for monitoring the level of systemic risk of the financial sector (which we denote GS for general systemic or simply systemic risk index), and a ranking for systemically important financial institutions, which we denote SIFIRank.

3 Systemic risk indexes and SIFIRank

Given the four points in previous section, a firm is systemically important if it is connected with strong transmission channels to many other firms, and if its strongest linkages are with other companies that are also systemically important. Let $S_{k\,t}$ be the systemic importance of firm k at time t, which depends on the importances of its connected peers:

$$S_{k\,t} = \sum_{j \in \mathcal{R}_{k\,t}} S_{j\,t} c_{k\,j\,t}, \tag{1}$$

where $\mathcal{R}_{k\,t}$ denotes the set of companies with a transmission channel to firm k at time t. The scale $c_{k\,j\,t}$ is the transmission weight between firms k and j:

$$c_{k\,j\,t} = \frac{\rho_{k\,j\,t}}{\sum_{i \in \mathcal{S}_{j\,t}} \rho_{i\,j\,t}}. \tag{2}$$

It represents the transmission channel (given by the strength) between companies k and j at time t scaled by the sum of the transmission channels between the company j and the rest of the system. Indeed, (1) can be written in matrix form as

$$\mathbf{S}_t = \mathbf{C}_t \cdot \mathbf{S}_t, \tag{3}$$

where $\mathbf{S}_t$ is the $N \times 1$ vector of systemic risk importances and $\mathbf{C}_t$ is the $N \times N$ transmission matrix that has zeros in the main diagonal, since a firm does not transmit risk to itself. The solution to (3) is the eigenvector associated with the largest eigenvalue of $\mathbf{C}_t$, which by construction is one.

This is the standard eigenvector centrality measure often used in network analysis. It does not incorporate firm characteristics – we introduce them below – as it only contains information about the transmission channels. This channel-only vector of importances is useful for the construction of a general index of systemic risk for the financial sector, which serves as a bird's-eye tool for monitoring purposes. As mentioned earlier, one of the features of the build-up of the financial crisis was the increase in system-wide risks. Indeed, the general index of systemic risk, denoted by GS_t, is based on the fact that as the strength of the transmission channels increases, the network becomes more dense, or, in terms of (3), the values in $\mathbf{S}_t$ increase. Let $\mathbf{S}_t^{Fin}$ be the subset of $\mathbf{S}_t$ that contains the N^{Fin} financial institutions. Then GS_t equals the average of $\mathbf{S}_t^{Fin}$:

$$GS_t = \frac{1}{GS_B} \sum_{k=1}^{N^{Fin}} \frac{S_{k\,t}^{Fin}}{N^{Fin}}. \tag{4}$$

The denominator GS_B inside the sum is a normalization which makes GS_t relative to a particular benchmark. We choose September 15, 2008 as the day on which the Lehman Brothers bankruptcy was announced to serve as this benchmark. This is the day after the announcement of a \$US3.9 billion loss, an important drop in its share value, and massive trade in Lehman shares (associated with large naked short-sales positions which led to the ban on short-sales in financial institution stocks implemented on September 19, 2008). Therefore if $GS_t = 1$ the general level of systemic importance at day t is as high as September 15, 2008.[2]

[2]Alternatively we can normalize by $max_{t' \le t}(GS_{t'})$:

$$GS_t = \frac{1}{max_{t' \le t}(GS_{t'})} \sum_{k=1}^{N^{Fin}} \frac{S_{k\,t}^{Fin}}{N^{Fin}}.$$

Firm characteristics are known to play an important role in ranking systemically important financial institutions: a large, leveraged and illiquid firm should be ranked high. Following Brownlees and Engle (2011), for firm k, the characteristics we use are i) size, measured as the market value of equity and denoted by $size_{k\,t}$, ii) leverage, measured as the debt to finance the firm and denoted by $lvg_{k\,t}$, and iii) liquidity, measured as the assets that can be quickly transformed in cash and denoted by $liq_{k\,t}$. Moore and Zhou (2012) use a similar set of indicators. We gather these firm characteristics in the vector $\mathbf{fc}_{k\,t} = (size_{k\,t}, lvg_{k\,t}, liq_{k\,t}^{-1})$, and each company index gains further weight from these features:

$$S_{k\,t} = \alpha \sum_{j \in \mathcal{S}_{k\,t}} S_{j\,t} c_{kj\,t} + \boldsymbol{\omega}' \mathbf{fc}_{k\,t},$$

where $\boldsymbol{\omega}$ is a vector of positive weights that regulates the contribution of the firm characteristics, and $\alpha < 1$ is a scaling that weights the relative contribution of the network. The balance between the contributions of the network and the firm contributions is therefore given by α and $\boldsymbol{\omega}$. In vector form

$$\mathbf{S}_t = \alpha \mathbf{C}_t \cdot \mathbf{S}_t + \boldsymbol{\omega}' \mathbf{fc}_t.$$

The solution for the systemic risk importances at time t is:

$$\mathbf{S}_t = (\mathbf{I} - \alpha \mathbf{C}_t)^{-1} \boldsymbol{\omega}' \mathbf{fc}_t. \tag{5}$$

This is an enhanced and adapted version of Google's PageRank that, in turn, stems from the measure of eigenvector centrality used for the construction of GS_t. The numerical values of the vector of financial systemic importances do not have an absolute interpretation, but their ranking has a relative interpretation. This leads to our ranking metric:

$$\mathbf{SIFIRank}_t = \text{rank}(\mathbf{S}_t^{Fin}).$$

This is a neat and readily interpretable expression.[3] We now see that, besides a simple

The normalization makes GS_t relative to the most systemic day in the sample history. If $GS_t = 1$ the general level of systemic importance at day t is the highest in the sample, otherwise $0 < GS_t < 1$. In our sample, normalizing by GS_B or $max_{t' \leq t}(GS_{t'})$ gives almost the same result. The most systemic day of the sample is September 11, 2008, and on our benchmark date of September 15, 2008 the index is just 0.1% lower than if we used September 11, 2008.

[3] An alternative dynamic scaling may be useful when the overall levels of systemic risk are changing: $\mathbf{SIFIRank}_t^* = \frac{\mathbf{SIFIRank}_t}{GS_t}$. Although this metric can take non-integer values, a firm with rank 1 indicates not only that it is the most systemic at time t, but also that the systemic risk level of the financial sector

interpretation, the methodology we propose has the following advantages: the ranking metrics are straightforward and quick to calculate with no need for optimizations, and they take into account linkages between the financial sector and the real economy while incorporating firm characteristics.

4 Data

The results in this paper are based on a newly compiled high frequency data set on high frequency returns in the component stocks from the S&P500 index. The details of this new dataset are briefly explained in the following sub-section, before proceeding to the descriptive statistics for the network results.

Data handling

The raw data consist of 5 minute observations downloaded from the Thomson Reuters Tick History for all RIC codes included in the S&P500 provided by SIRCA for the period January 1, 2002 to December 31, 2011. The initial download contains 935 tickers.[4] The dataset used in this paper does not purport to be a full history of all stocks on the S&P500, but rather draws from the universe of S&P500 listed companies for the period 2002–2011. Stocks enter and leave the dataset, and at various times there are observations missing for a myriad of reasons (stock halts for example).[5] After this process the sample contains 557 stocks.

As our methodology is best applied to a balanced panel of stocks we first truncate our sample to begin in January 2003, as there are considerable numbers of stocks which did not have full data in the earlier years. We then have data of three types: stocks which are present throughout the entire sample, stocks which leave part way through the sample, and stocks which enter partway through the sample. Additionally, some stocks have days of missing values at various points (usually due to stock splits or similar events) and we

is as high as the benchmark day. In our system $\mathbf{SIFIRank}_t$ and $\mathbf{SIFIRank}_t^*$ do not differ substantially and thus we focus on $\mathbf{SIFIRank}_t$.

[4]The SIRCA stocklist '0#.SPX' contains many more stocks than actually trade including OTC and alternative exchanges. We retain stocks with suffixes N,K and OQ which represent the NYSE, NYSE (Amex) Consolidated and Nasdaq respectively. We remove stocks which altered currency of trade during the period and adjust for changes in RIC code. There is no unique code which traces a single stock through time – unlike the unique company or stock numbers found in COMPUSTAT – so we match codes and companies through merger and acquisitions, stock splits and trading halts.

[5]Our process is documented in the web-appendix to the paper. Programs in C+ are available on request to both replicate the data and make alternative selections.

drop a small number of stocks with insufficiently complete data. We then choose to force inclusion of three stocks which would not have made it through this data cleaning process: these were Lehman Brothers (who were delisted in 2008 after becoming bankrupt), Fannie Mae, and Freddie Mac. Following their placement into conservatorship on September 6, 2008, the ordinary stocks of Fannie Mae and Freddie Mac were no longer traded on the exchange. We use data from alternative markets, mainly OTC and NYSE Arca for the intervening periods between the cessation of the listed stocks and the emergence of a steady stream of OTC Bulletin Board data from after their return to government status. At the final stage there are 502 time series for stocks in the database, from January 2, 2003 to December 30, 2011, for a total of 2262 trading days. The complete list may be found in the web-appendix.

Computing the shocks

Using the last trade in each 5 minute period between 9:30am and 04:00pm each trading day we construct annualized daily realized volatilities as the sum of squared intradaily returns, with overnight returns removed. These realized volatilities form the basic dataset, $x_{j\,t}$. More precisely, let $r_{j\,t\,i}$ be the intraday trade return of firm j on day t at 5-minutes time $i = 1, \ldots, N$. The annualized realized volatility is

$$x_{j\,t} = 100\sqrt{252}\sqrt{\sum_{i=1}^{N} r^2_{j\,t\,i}}.$$

This is the simplest estimator of the integrated volatility from high frequency data, and is valid if prices follow a Brownian motion.

If prices have a jump component this will be incorporated into $x_{j\,t}$; see Barndorff-Nielsen and Shephard (2004). While the inclusion of jumps in a measure of integrated volatility is a disadvantage for analyses that focuses on volatility, this is an advantage in our case. Jumps are a distinguishing feature of asset pricing under stressful conditions and occur in response to information as shown in Dungey et al. (2009), Lahaye et al. (2011), Andersen et al. (2007), and thus their inclusion is practically important in attempting to empirically model systemic risk. While the estimator is in principle contaminated by microstructure noise, 5-minute data is the commonly used benchmark trade-off between information and noise for liquid assets; see for example Lahaye et al. (2011) and Andersen et al. (2007).[6]

[6] As yet there is no methodology for choosing optimal sampling frequency when working with multiple

To obtain the volatility shocks, v_{it}, we filter the realized volatilities with ARFIMA models. This choice is motivated by Andersen et al. (2001), Andersen et al. (2003) and Luciani and Veredas (2011). They show that the ARFIMA$(1, d, 0)$ is an accurate representation of the long-memory stylized fact of realized volatility. Last, the sample transmission matrix is computed as in (2). To minimize the uncertainty due to the estimation error, sample correlations are tested for the null hypothesis of zero. If this cannot be rejected, they are set to zero.

A description of the interconnections

Drawing on the estimated connections, we provide summarized statistics on the proportion of connections and their strength. The top plot of Figure 1 shows the evolution of the fraction of companies to which any firm is connected, whereas the bottom plot shows the dynamics of the connections strengths. For each plot, a point on the middle line is the cross-sectional median, while the interval is the cross-sectional 25% and 75% quantiles, reflecting the heterogeneity in the connections at any point in time.

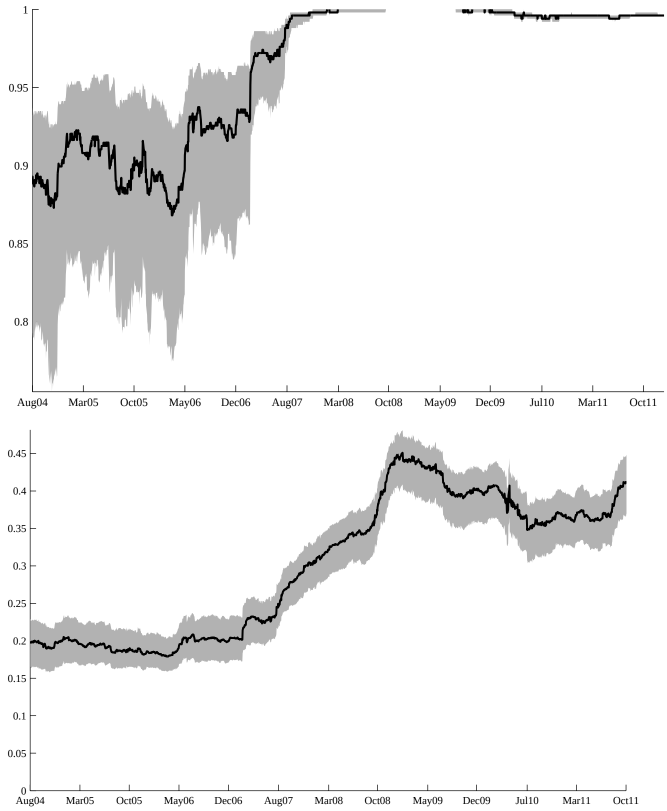
The network is highly connected. At the beginning of the sample, a median around 90% of the connections are different from zero with a great deal of heterogeneity. The fraction of connections increases steadily from mid 2006 onwards to reach a fully connected network around August 2007. This dovetails with the bottom plot, which shows that during the beginning of the sample the strength of connections is relatively low – a median correlation around 0.2 – and it increases steadily from August 2007 onwards to reach 0.45 at around January 2009. Then there is a slight decrease in the strength of the connections, which remains in the interval 0.35-0.40 until the end of the sample.

Figure 2 complements the analysis. It provides network diagrams that emphasize the connection of the financial sector with the rest of the economy for four days of the sample period: May 1, 2006, November 1, 2007, September 12, 2008, and December 30, 2011. The first date is prior to the crisis, the second is at the beginning of the build-up of global risks that lead to the upheaval, the third is the working day prior to the bankruptcy of Lehman, and the fourth is the last day of the sample. For comparison we also show, in lighter color, the connections between the other sectors.

The node of each sector has two dimensions: its radius is the number of firms and the color scale reflects the median strength between the firms that belong to the sector (the darker the more connected). The width of the edges between sectors denotes the strength

assets.

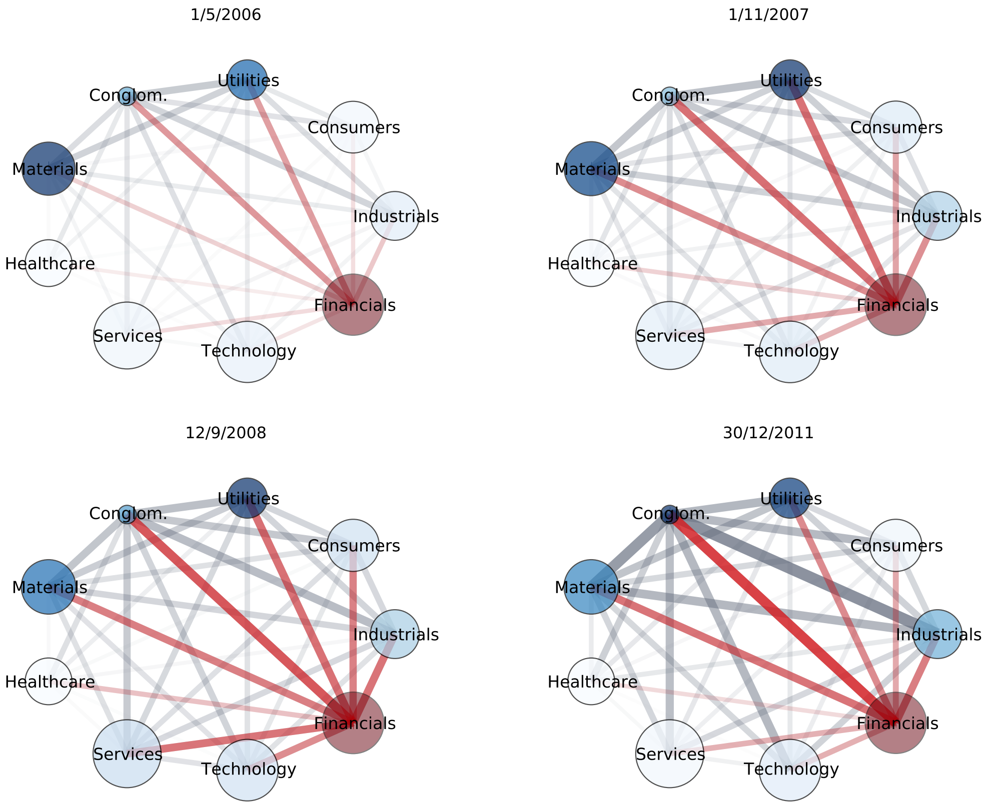
Figure 1: Fraction of connections and their strength – all firms



The top plot shows the evolution of the fraction of companies to which any firm is connected, whereas the bottom plot shows the dynamics of their strengths. For each plot, a point on the middle line is the cross-sectional median, while the interval is the cross-sectional 25% and 75% quantiles.

(the wider the more connected). The sequence of plots reveals that the financial sector is the most important of the system: it is among the largest and more intra- and inter-connected. The number of firms per sector does not vary significantly, and neither does the intra-sector strength. However, and more importantly, the inter-sector connections have varied markedly, confirming the results of previous figures: prior to the build-up of risks, connections were relatively weak, but as time progressed they were reinforced and gained in importance. Indeed, the plots for May 1, 2006 and December 30, 2011 differ substantially. By the end of the sample all the sectors are more connected than ever before, highlighting both the changes that this crisis has promoted in the economy, and once more that the links between the financial sector and the rest of the economy cannot be ignored.

Figure 2: The network of financials with the rest of the economy



From top to bottom and from left to right, the networks correspond to the dates shown at the top of the each plot. The node of each sector has two dimensions: its radius is the number of firms and the color scale reflects the median strength between the firms that belong to the sector (the darker the more connected). The width of the edges between nodes denotes the strength (the wider the more connected).

Firm characteristics

The characteristics of each firm are represented with firm size, leverage, and liquidity. Data are obtained from Thomson Reuters Datastream. Size is measured by market capitalization, and observed daily. Leverage is defined as the book value of assets minus the book value of equity plus the market value of equity. As it uses both market and book-based information, it is available daily. Liquidity is book-based and described by the sum of cash and short term investments divided by the book value of assets, and is available every quarter.

These variables are very different in scale, and some standardization is needed. Let

$\text{Size}_{k\,t}$, $\text{Leverage}_{k\,t}$ and $\text{Liquidity}_{k\,t}$ be the firm characteristics as explained above for firm k at time t. Then:

$$
\begin{aligned}
size_{k\,t} &= \frac{\log \text{Size}_{k\,t}}{\sum_{j=1}^{N} \log \text{Size}_{j\,t}}, \\
lvg_{k\,t} &= \frac{\log \text{Leverage}_{k\,t}}{\sum_{j=1}^{N} \log \text{Leverage}_{j\,t}} \qquad \text{and} \\
liq_{k\,t}^{-1} &= \frac{\log \left|\text{Liquidity}_{k\,t} - 1 - \max_j \text{Liquidity}_{j\,t}\right|}{\log \left(1 + \max_j \text{Liquidity}_{j\,t}\right)}.
\end{aligned}
$$

The standardization on size and leverage is via cross-sectional averages, so the cross-sectional means of $size_{k\,t}$ and $lvg_{k\,t}$ are one for every t. The transformation for liquidity, $liq_{k\,t}^{-1}$, is more involved since the ratio of cash and short term investments over the book value of assets can be negative. The standardization is therefore with respect to the maximum.

Implementation: practical aspects

In order to compute the time variation in the transmission matrix we consider a rolling window. We start with the realized volatilities and firms characteristics of the first 400 days (roughly 1.5 years; the first window begins on January 2, 2003 and ends on August 10, 2004), compute the shocks, their correlations, the firm characteristics, GS_1 and SIFIRank_1. We then roll the window one observation and the process is repeated until the end of the sample (the last window starts on June 3, 2010, and ends in December 30, 2012), making a total of 1863 windows.

Regarding the choice of the network and firms characteristic contributions, we set $\alpha = 0.66$, $\omega_{size} = 0.4$, $\omega_{lvg} = 0.4$ and $\omega_{liq} = 0.2$. The choice of 0.66 for α is based on calibration (Google suggests 0.85 for solving the problem of dangling websites), while the choice of $\omega_{liq} = 0.2$ is to avoid large discontinuities in SIFIRank as the balance sheet data are released every quarter. The choice of α and $\boldsymbol{\omega}$ do not affect calculations of GS_t where $\alpha = 1$ and $\omega = 0$. Robustness to different choices for α and $\boldsymbol{\omega}$ for individual firm results are available in the web appendix.

5 The great financial crisis, and beyond

5.1 Systemic risk indices

The plot of the GS_t index (4) is given in Figure 3. It reaches its peak on the day deemed most risky in the sample – which in this case is September 11, 2008. It follows a week of growing stress in the financial system which included the Federal takeover of Fannie Mae and Freddie Mac. The week following the peak, prior to the filing of Chapter 11 for Lehman, was a period of intense speculation as to whether regulatory intervention would occur. Tensions remained very high in the period until September 23, 2008, following the bailout of AIG (September 16); this period has been pinpointed as the most risky in at least 25 years in Nishiyama and Iiboshi (2011).

From September 23, 2008 our index shows that the systemic risk in the financial sector began to decline. While on this same day the S&P500 fell by over 400 points and a record daily price rise for oil was recorded, the fall in systemic risk is consistent with adjustment of expectations concerning the ongoing effects of the crisis. At this time Congress was debating the extent of the proposed $US700 billion bailout funding first mooted by US Treasury Secretary Paulson on September 19. Subsequently, the announced approval of TARP on October 3, 2008, precipitated a sustained decline in the systemic risk index which lasted until the end of March 2010.

A reduction in systemic risk due to the TARP announcement is consistent with evidence of reduced perceptions of market risk and generosity of the program, compared with those implemented in European and British jurisdictions, in King (2011). In response to the rescue packages, US banks actually outperformed the general market. King (2011) interprets this as evidence for the general acceptance of stability of the system, as both banks which did and did not receive assistance had improved share market outcomes, although those who did not receive assistance were more strongly rewarded.

Systemic risk begins to increase again from April 2010, consistent with increasing concerns over emerging problems in European sovereign debt markets, and specifically Greece. While the first signs of Greece's problems emerged in late 2009, it was in the first quarter of 2010 that international financial markets were affected. The nadir of the GS index occurs around 15th April, which is after the EU bailout package was announced, but before the call for IMF assistance on April 23. The rise in risk seems likely to be related to realization of the severe contagion risks associated with potential escalation of the crisis and the estimated larger combined exposure of the international banking sector to Greece, Portugal and Spain (see "Still in a Spin", *The Economist*, April 15, 2010).

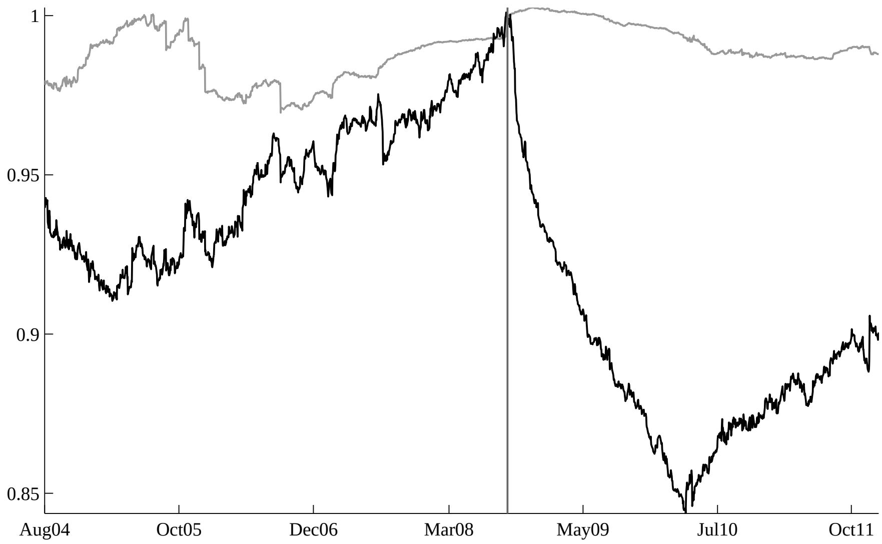
Figure 3: SYSTEMIC RISK INDEX GS_t

The importance of macro-financial linkages

Thus far we have provided evidence of the evolution of systemic risk in the US financial sector taking into account interlinkages between companies from a wide range of sectors. As the existing literature generally considers only linkages between financial firms, we provide further evidence by considering indices where real economy interlinkages are ignored. We adopt the notation of GS_{MF} for the index that takes into account the macro and financial linkages, previously denoted simply as GS. We also construct a financial sector index, denoted GS_F, which uses only the set of firms in the financial sector as the base for calculating the measures, i.e. the vector $\mathbf{S}_t$ in (3) is of size N^{Fin} and only contains the financial firms (and hence the transmission matrix $\mathbf{C}_t$ only contains information about the connections between financial firms).

Figure 4 displays a distinctive widening of the gap between the GS_{MF} and GS_F over the whole sample, in particular post August 2008. Immediately following this period there is a strong drop in GS_{MF}, as previously discussed. However, the systemic risk measure which concentrates only on the interconnectedness of the financial sector does not display the same extent of drop. These gaps represent a change in the relative riskiness of the financial and real firms in the sample. It emphasizes how the interactions with the real economy influence perceptions of risk, as the descriptive Figures 1 and 2 suggested. The

Figure 4: With and without real economy linkages



The black line is GS_{MF}, formerly simply GS, while the grey line is GS_F, i.e. the systemic risk index without incorporating the linkages of the financial firms with the rest of the economy.

intervention policies enacted in September and October 2008 were exceptionally effective in disconnecting the financial sector from the real economy – investors no longer perceived that the financial sector was spiraling downwards. Although damage to the real economy was already in place, the measures show that the decline in the financial sector was effectively halted *relative to* the real economy firms. The GS_F index does not display the same fall because the policy interventions did not alter the relative riskiness or interconnectedness of the financial sector itself. Thus, in assessing the policy interventions one can draw the conclusion that if the aim was to halt the spread and amplification of the crisis occurring via the interconnectedness of the financial sector and real economy, then this should be deemed to have been successful – while it did not materially change the structure of the connections in the financial sector itself.

5.2 SIFIRank

Bucketing SIFIRank

To analyze the dynamics of the individual firms we opt for the bucketing approach of the Basel Committee on Banking Supervision (2011), henceforth BCBS, that proposes a methodology to classify global systemically important bank (G-SIBs). They consider five firm characteristics and construct a systemic importance score, ranging from 0 to 5. The calculated scores are assigned into four buckets which represent increasing levels of additional loss absorbency requirements for these institutions. An additional top fifth empty bucket provides incentives for banks to avoid becoming the most systemically important. The additional loss absorbency for the top empty bucket is 3.5% of risk-weighted assets, and it reduces progressively in the subsequent buckets, up to 1% for the first bucket.

This bucketing approach is a convenient way to summarize results. Indeed Table 1 shows SIFIRank in four buckets. Each year is divided in two semesters (S_1 and S_2), presented in the columns. For each semester, we check for each firm if at least 80% of the days ranks in the top 5 (bucket one), between the top 5 and 10 (bucket two), between the top 10 and 20 (bucket three), and between the top 20 and 30 (bucket four). The number 1 in the table means that the corresponding firm on the given semester is classified in bucket one. Likewise, the number 2 means that the corresponding firm on the given semester is classified in bucket two, and equivalently for 3 and 4.

Using the BCBS approach, the Financial Stability Board (FSB) has identified a list of globally systemically important banks, with information up to December 2009. The US based institutions they identify as globally important which occur in our sample are the Bank of America, the Bank of New York Mellon, Citibank, Goldman Sachs, JP Morgan, Morgan Stanley, State Street and Wells Fargo. One may think that this list is only partly comparable to ours since their system is the global banking system whereas ours is the US financial sector. However, within the same geographical scope as our analysis, the Federal Deposit Insurance Corporation (FDIC) requires resolution plans – or living wills – for systemically important financial institutions. In 2012, the US banks in the FDIC list are the same as those listed by the FSB.[7]

Three main conclusions emerge from the table. First, we find that all of the institutions identified by the BIS and the FDIC consistently appear in our buckets covering the top 30 firms by SIFIRank – that is they are SIFI ranked in the top 30 firms on no less than 80 percent of the days in the sample. Bank of America, Goldman Sachs, JP Morgan and Wells Fargo are consistently in the top 10, while Citigroup and Morgan Stanley sometimes rank outside the top 5 but always inside the top 20, and Bank of New York Mellon and State Street – two custodian banks – generally rank outside the top 10. Additionally, we identify the ranking of Lehman Brothers during the period they exist as consistently in the top 10 institutions by SIFIRank, and on a number of occasions in the top 5.

Second, Wells Fargo and JP Morgan spend a substantial proportion of the sample period

[7]See www.fdic.gov/regulations/reform/resplans for more details

Table 1: Bucketing SIFIRank

	2005		2006		2007		2008		2009		2010		2011	
	S_1	S_2	S_1	S_2	S_1	S_2	S_1	S_2	S_1	S_2	S_1	S_2	S_1	S_2
ACE Limited						4	4							
AFLAC									4	4	4	4	3	3
American International Group	4				4	2	2							
The Allstate Corporation		4		4		4	4	3	3	3	4			
Avalonbay Communities										4				
American Express Company	3	4	4	4	4		4	3	2	1	2	4	4	3
Bank of America Corporation	2	2	2	2	2	1	1	1	1	1	1	1	1	4
BB&T Corporation				3	1	2	1	3	4					
Franklin Resources	4			4	3	3	3			4	3	4	3	4
Bank of New York	4	4	4	4	4		4	3	1	2	3	4		4
Boston Properties									4	3				
Citigroup	1	2	2	2	3	3	2	1	4	4				
The Chubb Corporation		4	3	3	4	4		4	3	3	3	4	4	
Cincinnati Financial Corp	4	4							4	3	3	2	3	4
Comerica	3	4	3	3	3	3	4	4						
Capital One Financial Corp	2	2	3	4										
Equifax											4		4	
Equity Residential										4				3
E*TRADE Financial Corporation					4									
Federal Home Loan Mtg					4	4								
The Goldman Sachs Group	1	1	1	1	1	1	1	3	2	1	3	3	3	
HCP											4	4		
Hartford Financial Services Group	3	4		4	4	3	4						4	4
JPMorgan Chase & Co	1	1	1	2	1	1	1	1	1	1	1	1	1	1
KeyCorp	3	2	2	1	2	3	4							
Loews Corporation	3								4	3	1	1	2	1
Lehman Brothers	2	2	1	2	1	2	2							
Lincoln National Corp						4	3	3					3	3
MetLife	4			4	3	3	2	4				2	3	1
Marsh & McLennan Companies													4	4
Morgan Stanley	2	3	3	3	2	2	2	4	4			3	2	3
M&T Bank Corporation		4	2	2	3	4	4							
Northern Trust Corporation		4					3	3	2	3	4			
Plum Creek Timber Co									4	4	3	4		
Principal Financial Group			4	3	3	3	3	3		4		4	3	2
Progressive Corp				4					4	2	2	4	4	4
PNC Financial Services Group	3	4	4	3	3	4	4	3	3	3	3	3	3	3
Prudential Financial		4			4	3	3					3	2	1
Public Storage									3	3	3	3	4	4
Regions Financial Corp	4	4	3	3	4	4	3	4						
Synovus Financial Corp	4	3	2	2	3	3								
Simon Property Group								4	4	4	4	4	4	4
SunTrust Banks	4	3	3	2	3	4	4	4						
State Street Corp	4	4	3	3	4	4	4	3	3	3	4	4	4	4
Torchmark Corp	3							4	4				4	3
T Rowe Price Group		4	4							4	4	3	2	2
Unum Group									3	2	2	2	3	3
US Bancorp	3	3	3	3	4	4	3	3	3	3	3	3	2	2
Vornado Realty Trust									4	3	4	4		
Wells Fargo & Company	1	1	1	1	2	2	3	2	2	2	2	1	1	1
Weyerhaeuser Co	3	3	3	4							4	3	4	
Zions Bancorp			4	4										

This table summarizes SIFIRank by means of the BCBS bucketing approach. Each year of the sample is divided in two semesters (S_1 and S_2), as it is presented in the columns. For each semester, we verify for each firm if at least 80% of the days ranks in the top 5 (bucket one), between the top 5 and 10 (bucket two), between the top 10 and 20 (bucket three), and between the top 20 and 30 (bucket four). The number 1 in the table means that the corresponding firm on the given semester is classified in bucket one, and likewise for 2, 3 and 4.

amongst the top 5 most systemically important institutions. This was consistently the case for JP Morgan throughout the sample, but has been more varied for Wells Fargo. However, since the crisis, Bank of America has had a much greater presence in the top 5 than previously. These three banks suffered less from the crisis. On the other hand, Goldman Sachs has reduced its relative systemic risk profile. Prior to 2008 it was consistently in the top 5 most systemically risky institutions, but is more recently outside not only the top 5, but also outside the top 10 institutions. This reduction in risk profile likely reflects its transformation to a bank holding company accepting deposits from November 2008. Citigroup has dropped a great deal in the rankings; prior to 2008 it was consistently within the top 20 firms, and oft–times higher, reflecting ongoing problems within the company. This came to a head in 2008 where it briefly soared to one of the 5 most systemically risky institutions. The US government rescue package saw its systemic risk index drop dramatically outside the top 20 firms, and subsequent to 2009 it has not consistently entered the top 30 firms according to our ranking.

Third, firms that enter the next 10 most systemic financial companies are generally more varied by period, with the exception of US Bancorp which is in the top 20 firms in every period in the table. It is notable, however, that during the build-up towards the crisis in January to October 2008 is the only period where AIG occupies a position in this ranking. While we have noted some key firms, which are consistently evident in the most systemic companies, a firm such as AIG can come from much further down the ranking to have an important systemic effect and still be deemed 'too big to fail'.

Fourth, it is worth noting the emerging importance of insurance companies. AIG was in the top 10 (second bucket) companies during the 12 months from July 2007 to June 2008, but they do not reappear after the rescue in 2008. However, by the end of our sample, the insurance companies Loews, Metlife and Prudential appear increasingly in the buckets over the last years, and are in bucket 1 in the second semester of 2011.[8] Per se, insurance is a less threatening activity than banking for the financial system as a whole; see Prudential Regulation Authority (2013). Except for AIG, in the aftermath of the financial crisis there were no significant and negative collateral effects in the insurance sector. It has run and functioned normally and only experienced significant premium increases in response to random events such as hurricanes, earthquakes and floods.

The landscape may change if insurers venture into noninsurance underwritings due to

[8] Loews Corporation owns 90% of CNA, a commercial and casualty insurance company that is among the largest in the US, and about 63% of the total revenues of Loews in 2011, the most important business line of the Corporation.

voids left by the exit of banks from some areas. New regulatory and capital structures in banking entail the need for more liquidity and for banks to reduce their exposure to riskier business lines. Insurance companies may be tempted to enter these areas as an avenue for investing their liquid cash. Examples include insurance credit in real estate noted in Allen and Overy (2012), transforming ineligible to eligible collateral for the banking sector, and infrastructure debt. That is, insurance companies may increasingly act as shadow banks and contribute to the systemic risk of the financial sector.

Comparing SIFIRank and SRISK

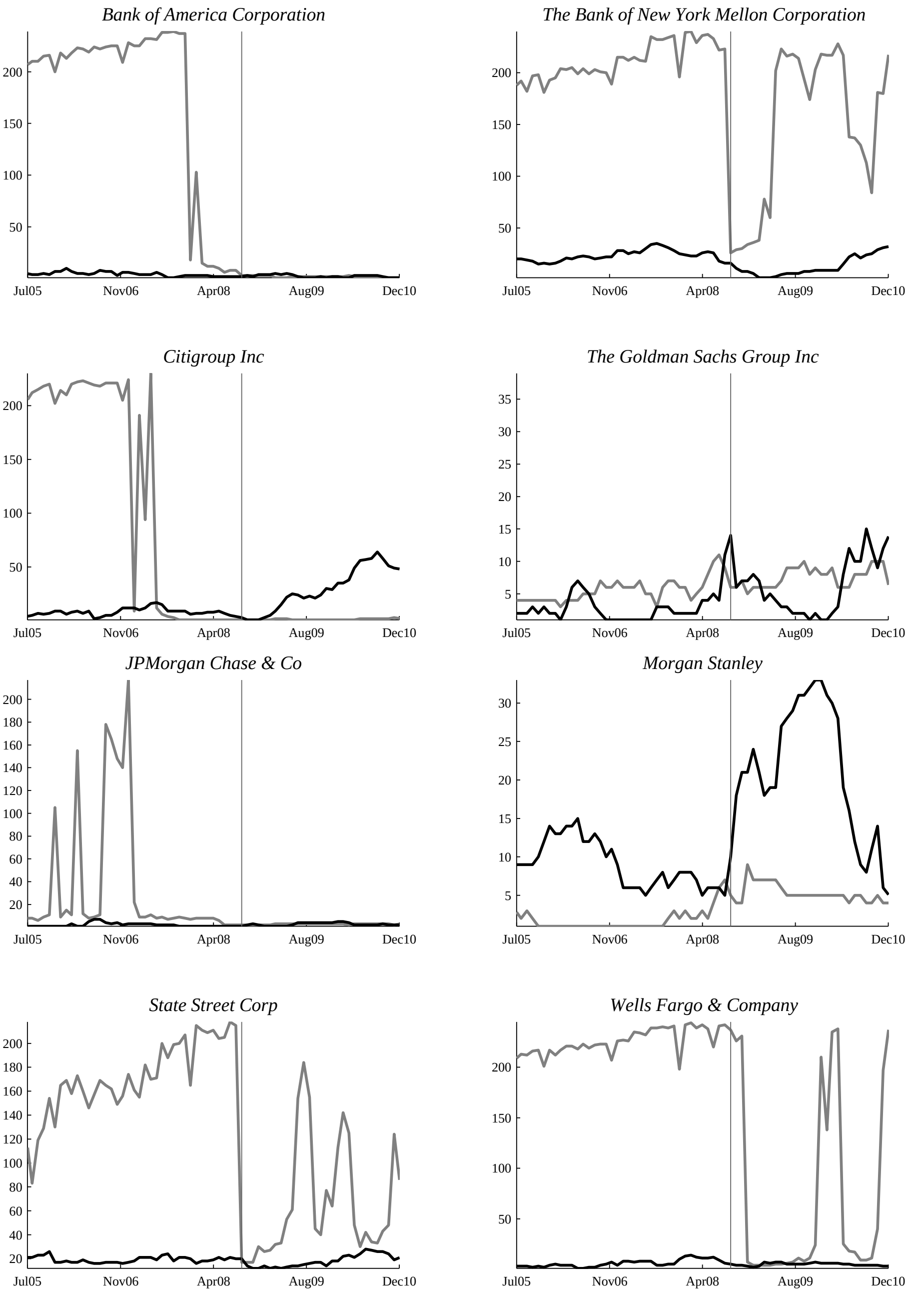
We compare the interconnectedness results with the ranking of SRISK by Acharya et al. (2010). We take advantage of the publicly available Stern V–Lab data (accessible at http://vlab.stern.nyu.edu) which provides individual systemic risk rankings for financial firms. We extracted these rankings for comparison with those generated in the previous section for individual firms, and we have drawn from the two databases the financial firms which are covered in both studies.

Figure 5 compares the rankings for the US banks deemed as systemic by the FSB and FDIC. It is readily apparent that many of the banks rank far higher (that is are indicated as less systemically risky) in the SRISK rankings than they do in SIFIRank. This is particularly the case in the pre-2007 period. Our index tends to show that these institutions are creeping towards the more systemically risky end of the scale (that is their rank is a lower number) from 2006 onwards. SRISK, in contrast, shows that these firms were often ranked over 200 amongst all the firms considered pre-2007, and in some cases pre-2008. Citigroup, Bank of America and JP Morgan provide good examples. Focusing on Citigroup, in the first six months of 2007, its systemic ranking fluctuated from positions 224, 9, 191, 94, 230, and 12 in consecutive months before settling into the top 10 most systemically risky firms. Other banks showed abrupt changes in their ranking around the period of late 2008 and post-crisis, such as Bank of New York Mellon, State Street and Wells Fargo.

Goldman Sachs and Morgan Stanley present a somewhat mixed picture but are usually in the top 20 for both measures – the DLV interconnectedness measure proposes that there are periods when these firms are less highly ranked than SRISK implies.

An important facet of the individual comparisons for these risk measures is the at times extreme fluctuations in the SRISK rankings compared with the relatively smoother path of SIFIRank. This volatility arises due to large unexpected changes in capital and debt, as

Figure 5: SIFIRank vs. SRISK ranking



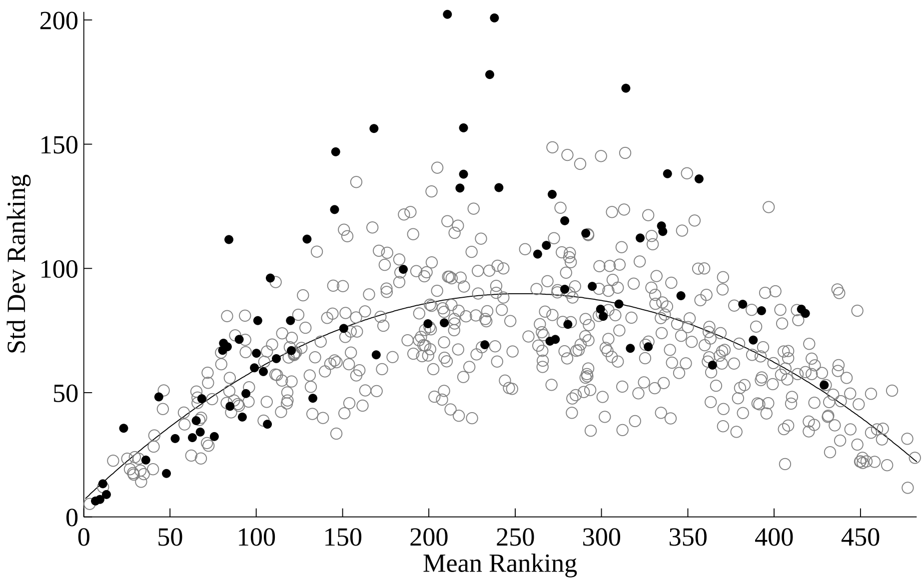
Black lines represent SIFIRank whereas grey lines represent the SRISK ranking.

well as the inherent sensitivity of the tail analysis that is at the core of SRISK (as it is a function of the marginal expected capital shortfall approach of Acharya et al., 2010). By contrast, our more continuous and smooth methodology based on correlations provides a clearer direction for the changes in systemic ranking. We argue that the volatility in the capital shortfall measures makes it difficult for policy makers to use these measures due to their concern with false signaling – for example, has Wells Fargo really moved from the status of non-worrying to top 10 and back again twice in the space of less than two years – and how should a policy maker act on such information?

The Boomerang Curve

Figure 6 provides a scatterplot of the average of the ranking (rank($\mathbf{S}_t$)) for each of the 502 firms in the system, for an individual firm (horizontal axis) against the standard deviation of its ranking (vertical axis). The open circles represent the non-financial firms while the filled circles are the financials. Due to its obvious likeness we dub the graph the *boomerang curve.*

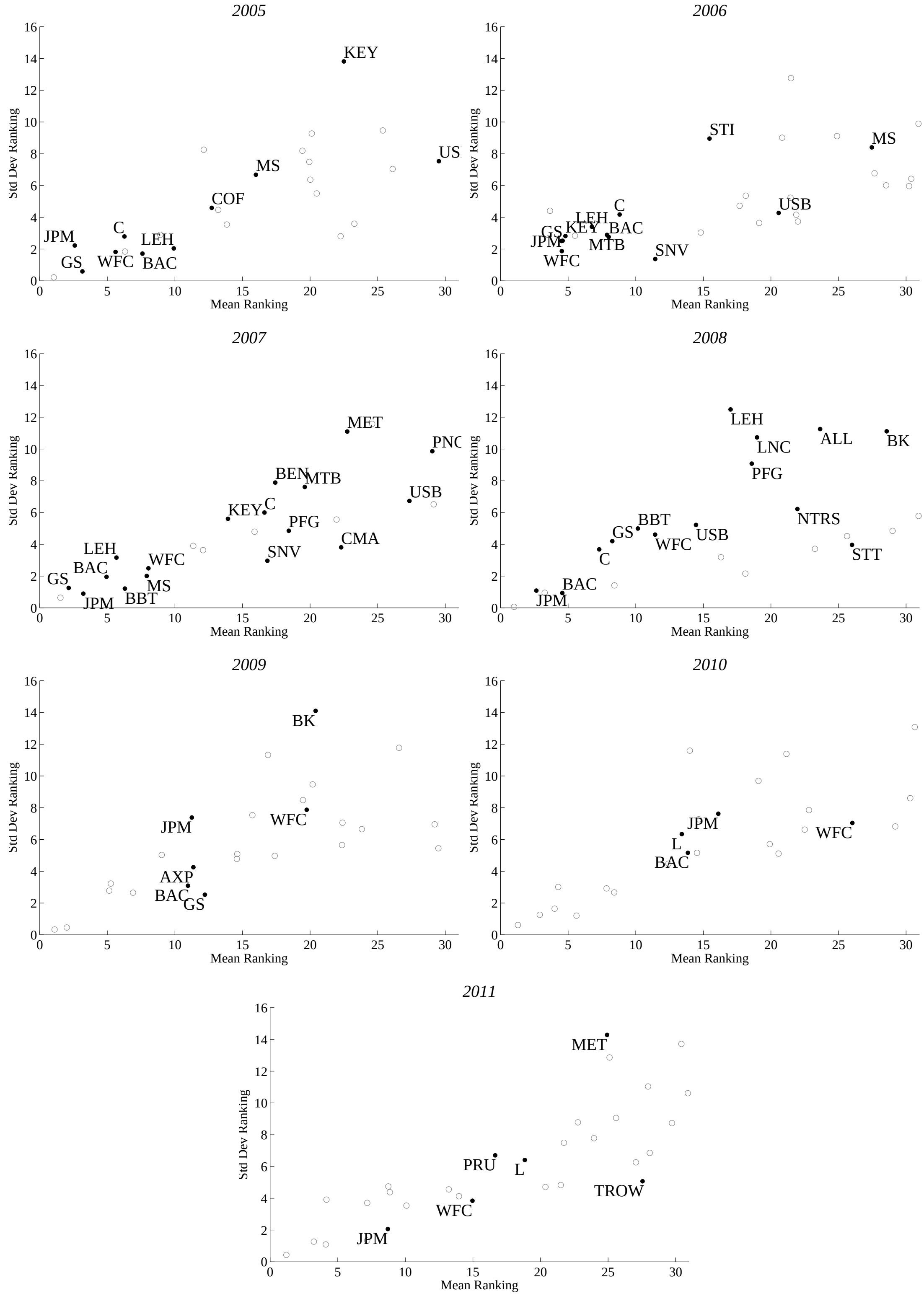
Figure 6: BOOMERANG CURVE



Black circles represent financial firms. Open circles represent non-financial firms. The curve is a simple quadratic plot of best fit through the data.

There are two areas of the boomerang curve that are likely to be of interest to regulators. The first is the area of firms at the left end of the boomerang curve. These firms are

Figure 7: Boomerang curve. Zoom and year by year



Black circles and the labels represent financial firms. Open circles represent non-financial firms.

consistently ranked amongst the most systemic – and they do not often fall out of this category. Closest to the origin we find four banks: JP Morgan, Wells Fargo, Bank of America and Lehman Brothers. Of these, clearly Lehman did not survive the crisis events of 2008. The three remaining banks are some of the largest by customer base and capitalisation in the US. They are also identified as Global SIBs by the Basel Committee on Banking Supervision (2011, 2013) rankings and as systemically important by the FDIC. Thus there is strong agreement amongst different approaches that these banks pose substantial systemic risk to the economy. The second area of potential macroprudential policy concern corresponds to firms which have ranking somewhere near the middle of our sample, but with high standard deviation. That is they are near the apex of our boomerang. These firms generally present as not particularly systemically important but their situation may change rapidly. They include firms such as the insurers AIG, and banks like Keycorp, Synovus and the financial conglomerate Regions Financial Corp.

Figure 7 provides the left hand end of annual boomerang curves for each year in our analysis, zooming in the quadrant 30 (horizontal axis) by 15 (vertical). Individual financial institutions are marked on each plot. In 2005(2006) there were 10(11) financial institutions in the indicated region including those already mentioned above, but this built dramatically in 2007 to 17 institutions. Essentially, there were a new set of entrants in this area of the curve, consisting of institutions including BB&T (BBT), Franklin Resources (BEN), Comerica (CMA), Prudential Financial Group (PFG), Metlife (MET), M&T Bank (MTB), and Synovus (SNV). The analysis clearly identifies that systemic risk in financial firms was growing in 2007. In 2008 there is an elevated number of financial firms continue to show systemic risk. From 2009 onwards the situation changes dramatically, with only 6 firms in the selected quadrant, dropping to 4 and 5 in 2010 and 2011 respectively. Consistent appearances amongst the most systemic firms are again made by JP Morgan, Wells Fargo and Bank of America. Loews (L) and Prudential (PRU) make an appearance in this category in the last two years of our sample (see footnote 7).

The boomerang curve provides an easily digested visualisation of the systemically important financial institutions drawing from the daily SIFIRank computed from a system of interconnected risks amongst the real and financial sectors in the US. It summarizes the analysis of the changing nature of the links between companies, and their characteristics, and their subsequent movement in ranking of systemically important firms. The results strongly suggest that this index indicated the emergence of both increasing systemic risk in the financial sector as a whole and identified the emergence of greater systemic importance of individual financial firms well in advance of the crisis events of 2008. Consequently, a measure of systemic risk via interconnectedness between the financial and real economy sectors as proposed in this paper may prove to be a useful tool for the arsenal of macro prudential regulation.

6 Conclusions

Trichet (2009) ended with the observation that the macroeconomic policy interventions into the 2008 crisis had a stabilizing effect. Using an interconnected system of risk shocks between financial sector and real economy firms we show the veracity of this statement. Policy interventions such as the TARP and the rescue of AIG halted the decline in the financial sector *relative* to the real economy firms. Thus in assessing the policy interventions one can draw the conclusion that if the aim was to impede the spread and amplification to the real economy, then this should be deemed to have been successful. However, these policy interventions did not alter the relative riskiness or interconnectedness of the financial sector itself.

To measure systemic risk in line with definitions from both policymakers and academics, our approach takes into account that firms are related by a system of risks, which may be affected by shocks that are transmitted through both the financial sector and the real economy. An adaption of the Google PageRank algorithm is used to account for the interconnections of firms in the economy, and allows a ranking of the most systemically important. Using equity market data – along with firm characteristics – facilitates a timely measure, with greater coverage than available when relying on bank level exposure data.

The evidence collected in this paper for US companies listed in the S&P500 strongly suggests the importance of two categories of firms. Firstly, those which consistently rank as the most systemic throughout the sample – including banks such as Wells Fargo, Bank of America and JP Morgan – and those which may on average rank in the middle of the system, but have the capacity for rapid change, such as AIG and KeyCorp. These firms are predominantly financial firms, reinforcing the regulatory emphasis placed on understanding and perhaps limiting the exposure of the economy to these institutions.

There are a number of important extensions which could be countenanced to this work. The first is widening the scope of the firms included in the analysis. This includes incorporating firms which do not trade in the S&P500 and those which are not even listed, perhaps using criteria such as assets under management. It also includes extensions beyond the

US, to incorporate cross-border financial institutions and the issue of global SIFIs. The second is the inclusion of a greater set of potential firm characteristics, and indeed different characteristics for different sectors, or sectors in different jurisdictions. Additionally, controls for macroeconomic conditions more generally may add further information. Finally, adapting this approach to consider leading and lagging correlations may enable us to examine mechanism for shock transmission and directionality in the system, consistent with the pair-wise Granger-causality approach in Billio et al. (2012) and Diebold and Yilmaz (2013).

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