Duisenberg school of finance - Tinbergen Institute Discussion Paper

TI 12-115/IV/DSF 44

Ranking Systemically Important Financial Institutions

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Abstract

We propose a simple network–based methodology for ranking systemically important financial institutions. We view the risks of firms –including both the financial sector and the real economy– as a network with nodes representing the volatility shocks. The metric for the connections of the nodes is the correlation between these shocks. Daily dynamic centrality measures allow us to rank firms in terms of risk connectedness and firm characteristics. We present a general systemic risk index for the financial sector. Results from applying this approach to all firms in the S&P500 for 2003–2011 are twofold. First, Bank of America, JP Morgan and Wells Fargo are consistently in the top 10 throughout the sample. Citigroup and Lehman Brothers also were consistently in the top 10 up to late 2008. At the end of the sample, insurance firms emerge as systemic. Second, the systemic risk in the financial sector built–up from early 2005, peaked in September 2008, and greatly reduced after the introduction of TARP and the rescue of AIG. Anxiety about European debt markets saw the systemic risk begin to rise again from April 2010. We further decompose these results to find that the systemic risk of insurance and deposit–taking institutions differs importantly, the latter experienced a decline from late 2007, in line with the burst of the housing price bubble, while the former continued to climb up to the rescue of AIG.

Keywords: Systemic risk, ranking, financial institutions, Lehman.

JEL classification: G01, G10, G18, G20, G28, G32, G38

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1 Introduction

The last crisis has identified systemic risk as the most important regulatory issue facing the international financial system and exposed weaknesses in our understanding of the linkages between the financial sector and other sectors of the economy. This article introduces a simple network–based measure of systemic risk for US financial firms, whilst paying equal attention to the interrelationships between those firms, their characteristics, and their links with the real economy.

There are many definitions of systemic risk in the extant literature. It has been defined as broadly as i) problems which impede the functioning of the financial system, Tarashev et al. (2010), ii) interconnectedness, generally coupled with a recognition that characteristics such as firm size or leverage are important weighting factors in such interconnections, Drehmann and Tarashev (2011), Billio et al. (2010) or iii) the failure of financial institutions through exposure to some form of unexpected shock which impacts all institutions simultaneously, Allen et al. (2010).[1]

Alternatively, policy makers often refer to systemic risk as the potential for a shock in one firm or sector to result in disruption or even collapse in other sectors of the economy; this approach is apparent in the Promisel Report from BIS (1992: p61), Jean–Claude Trichet's Cambridge lecture in 2009, and in the academic literature such as Rochet and Tirole (1996). The Bank of England *Systemic Risk Survey* conducted since 2009 (Burls, 2009), promotes systemic risk as some combination of these common and propagating shocks by asking respondents to identify what they perceive as the greatest threats to the UK financial system. Meanwhile, empiricists have attempted to get to grips with the matter through such means as modeling simultaneous defaults in large financial institutions, Huang et al. (2011), volatility spillovers in Diebold and Yilmaz (2011), expected capital loss or capital shortfall, Moore and Zhou (2012), 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 Archara et al. (2012). A critical building block is the rapid development of the network finance literature which has shown the importance of the form of the interconnectedness of financial institutions in propagating shocks; see for example Allen and Gale (2000), Freixas et al. (2000) and Gai and Kapadia (2010). Bisias et al. (2012) provide a comprehensive overview of the methodologies currently in use to measure systemic risk.

This paper draws elements from each of these advances to develop a ranking of the systemic risk of the financial sector, and individual firms within that sector. We examine the network of connections between over 500 US companies drawn from the S&P500 index for the period 2003–2011, weighting the importance of these connections both by their underlying strength

[1] In the most recent literature systemic risk has taken on a distinct identity from contagion effects which are now understood to measure the unexpected transmission of what ex–ante appeared to be idiosyncratic shocks. Contagion was sometimes considered as a part of systemic risk, for example Allen and Gale (2000), but this is now less often the case.

and also by firm characteristics. The importance of firm characteristics in understanding and measuring systemic risk has been promoted by the work of Moore and Zhou (2012), and Brownlees and Engle (2011).

Along with Schwaab et al. (2011) we emphasize that there are both cross–sectional and time dimensions to systemic risk. On one hand we wish to assess risks that arise from the interconnectedness of firms at particular points in time, the cross–section, whilst at the same time being aware of the dynamics of these relationships over time. In order to assess whether the entire system is becoming riskier, and potentially warrants regulatory or policy intervention, it is necessary to have a solid understanding of the usual behavior of the system under a multitude of different economic conditions. The linkages between the macroeconomy and the financial system have been emphasized by authors such as Kapadia et al. (2012) and Schwaab et al. (2011); the latter includes macroeconomic and industry level conditions to do this, but in the process sacrifice the frequency of their final outcomes to a quarterly index. In a fast–moving crisis situation a higher frequency index may be desirable.

The results in this article are twofold: a daily systemic risk index for the financial sector, and a daily ranking of systemically important financial institutions (SIFI) over time.

We show that the overall systemic risk in the US financial sector rose to a peak in September 2008 and was impressively and quickly reduced by the regulatory and policy actions which occurred in late September and early October. We are also able to differentiate the behavior of deposit–taking institutions from that of insurance companies by constructing sub–indices for those groups. The deposit–taking institutions had a peak in systemic risk far earlier in the sample period, apparently closely aligned with the turn in the market for mortgage backed securities following the stall of the housing market in late 2007. Following that episode systemic risk for these institutions broadly declined. Insurance companies, however, experienced increasing systemic risk right up to the eruption of the Lehman Brothers and AIG crisis events. The systemic risk for these institutions then declined substantially, but has shown signs of increasing again following the escalation of the Greek sovereign debt crisis in April 2010.

To examine individual firms we use the bucketing approach of the Basel Committee on Banking Supervision (2011) that assigns the systemic importance into four buckets representing increasing levels of additional loss absorbency requirements. The buckets represent the top 5, next 5, following 10, and finally those firms ranked from 21 to 30. We identify the top 10 most systemically important financial firms: Bank of America, JP Morgan, Goldman Sachs and Wells Fargo are consistently in that top 10 throughout the sample. 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 are present. Outside the top 10, but in the top 20, the firms that make a consistent appearance other than those already mentioned are US Bancorp, State Street, PNC Financial Services and Morgan Stanley. At the end of the sample insurance companies (Metlife, Prudential and Loews among others) emerge at the top as the most systemic.

In line with the many definitions there are also many suggested regulatory responses to systemic risk such as greater transparency in financial data, Landier and Thesmar (2011), tighter regulatory ratios such as for capital, liquidity or even leverage, and a call for new design based on recognition of the network and systemic properties of the financial system; Haldane and May (2011). Our results are helpful in detecting and measuring the extent of risk building–up in financial networks, and importantly their interlinkages with the real economy, thus providing tools with which to begin approaching such aim.

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 SIFI ranking and the 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. First we analyze the systemic risk indexes for the financial sector and the sub–sectors, follow by a study of the importance of the macroeconomic linkages. We then move to the ranking, focusing on a selection of firms, some of which played a crucial role in the development of the crisis. We end examining the influence of the firm characteristics in the ranking. Section 6 concludes.

2 Dissecting the components of risk

Along with a number of other authors (e.g. Schwaab et al. (2011)) this article defines systemic risk following Jean–Claude Trichet Clare Distinguished Lecture in Economics and Public Policy at Clare College, University of Cambridge, on December 10 2009. He defines systemic risk 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.*

In what follows we dissect this definition, extracting four points upon which we build the methodology in next section.

A system of risks We understand the morphological meaning of systemic risk as the network of risks, or measuring how risks among firms in the economy are connected via their transmission channels; for example Gai and Kapadia (2010). Our decision to model the network of risks instead of price or returns is motivated by the origin of the crisis. Prior to the upheaval, it was said that collateralized debt obligations (CDO) and credit default swaps (CDS) were efficient investment vehicles for diversifying risks. However, instead of sharing and spreading a given level of risk, CDOs and CDSs were progressively building–up system–wide risks; as shown in Nijsjens and Wagner (2011). In other words, the magnitude and density of the network of risks in the financial system increased. We therefore use risks measures within a network context as our data set, along with firm characteristics, as explained below. More precisely, we consider a dynamic undirected and weighted network of N firms, and we denote by $x_{i\,t}$ the risk for asset i ($i = 1, ..., N$) at time t ($t = 1, ..., T$).

Risk shocks Trichet's definition starts by acknowledging that a crucial component of systemic risk are the *threats* in 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 network of shocks in risks rather than of risks themselves. The shock for asset i at time t is denoted by $v_{i\,t}$ and is obtained by means of a dynamic filter, denoted by $C_i(L)$. That is today's risk $x_{i\,t}$ is explained by all past shocks: $x_{i\,t} = C_i(L)v_{i\,t}$. Note that, conditional on information up to $t-1$, the covariance between risks and between shocks is the same: $Cov(x_{i\,t}, x_{j\,t}|\mathcal{I}_{t-1}) = Cov(v_{i\,t}, v_{j\,t}|\mathcal{I}_{t-1})$.

The financial sector and the real economy The last part of Trichet's definition acknowledges that the financial and the real sectors 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 object of interest is the relations between shocks in risks not only within financial firms but also between financials and non–financials. The way these relations are modeled is with a network where the strength of the transmission channels between all firms are given by the conditional correlations $\rho_{i\,j\,t} = Corr(x_{i\,t}, x_{j\,t}|\mathcal{I}_{t-1}) = Corr(v_{i\,t}, v_{j\,t}|\mathcal{I}_{t-1})$.

Common and idiosyncratic shocks In another passage of Trichet's lecture, he alludes to the *ways in which financial events are transmitted so widely that the fallout reaches systemic dimensions*. Following Bandt and Hartmann (2000) and Bandt et al. (2009) these include: i) The abrupt unwinding of wide spread financial imbalances; ii) negative aggregate shocks that affect all firms in the economy simultaneously; and iii) contagion effects due to the unexpected transmission of a shock in one firm leading to shocks to others. These three channels of transmission imply that systemic risk has common (the first two), and idiosyncratic (contagion) natures, all contained in $v_{i\,t}$. To see this, let u_t and $\varepsilon_{i\,t}$ be the common and idiosyncratic shocks respectively. Then $x_{i\,t}$ admits a factor representation:

$$x_{i\,t} = \lambda_i A(L)u_t + B_i(L)\varepsilon_{i\,t}.$$

Substituting in $x_{i\,t}$ for $v_{i\,t} = C_i(L)^{-1}x_{i\,t}$

$$v_{i\,t} = \lambda_i C_i(L)^{-1}A(L)u_t + C_i(L)^{-1}B_i(L)\varepsilon_{i\,t}.$$

And the covariance, conditional on information up to $t-1$, is:

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

The higher the contagion (i.e. the covariance between $\varepsilon_{i\,t}$ and $\varepsilon_{j\,t}$) and/or the volatility of financial imbalances and negative aggregate shocks (i.e. the variance of u_t), the higher the interconnection between the risk shocks of firms i and j.

In the next section we introduce a network–based 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

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 the firm that ranks in the k–th position 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. Note that since $\sum_{i \in \mathcal{S}_{j\,t}} c_{i\,j\,t} = 1$, $c_{k\,j\,t}$ can be seen as the $(k\,j)$ component of a transition matrix of a Markov chain of order one. 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 denser. Or, in terms of (3), an increase of the values in $\mathbf{S}_t$. 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. The rationale behind this benchmark is that it represents the most systemically risky day in the sample when a relative denominator is chosen. We choose September 11, 2008. 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 shocks implemented on September 19, 2008). Therefore if $GS_t = 1$ the general level of systemic importance at day t is as high as September 11, 2008.[2]

Since $\mathbf{S}_t^{Fin}$ is a subset of $\mathbf{S}_t$, we can choose another financial subset and easily construct systemic risk indexes for financial sub–sectors, such as deposit–taking institutions and insurance companies. Take, for instance, deposit–taking institutions and let $\mathbf{S}_t^{Dep}$ be the subset of $\mathbf{S}_t^{Fin}$ that contains these institutions. The deposit–takers systemic risk index is the average of $\mathbf{S}_t^{Dep}$:

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

Note that the normalization is the same as in (4), so the maximum and minimum between the financial sector GS index and their sub–sectorial counterparts are comparable.

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

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

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

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 the same result as the most systemic day of the sample is September 11, 2008.

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 the 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:

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

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

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

This is a neat and readily interpretable expression. However, it does not consider the general level of systemic importance: being at the top of the ranking in a period of low general systemic risk is not comparable with being at the top in a period of high general systemic risk. A dynamic re–scaling that adapts to the circumstances is required, which is done by using GS_t:

$$\mathbf{SIFIRank}_t^* = \frac{\mathbf{SIFIRank}_t}{GS_t}. \tag{6}$$

This is our second metric for ranking systemically important financial institutions. While, because of the scaling, (6) takes values other than integers, it has however an unambiguous reading: a firm with rank 1 at time t means that it is the most systemic and the level of systemic risk in the financial sector is the highest in the sample history. The extent by which $\mathbf{SIFIRank}_t$ and $\mathbf{SIFIRank}_t^*$ differ depends on the evolution of GS_t. If it does not vary too much over the sample period, both rankings will provide the same qualitative information, specially for firms that rank at the top.

We now see that, besides a simple interpretation, the methodology we propose has the following advantages (some of them previously highlighted): 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

In this section we first explain issues related with the handling, treatment and cleaning of the raw data. The second part describes how the shocks in risks are defined and computed. Next we present network–based descriptive statistics for understanding the underpinnings of the strength of the linkages and how they evolve over the sample period. The last two parts of the section are short and deal with the construction of the firm characteristics and practicalities regarding the implementation of the methodology.

Data handling

The raw data consist of 5 minute observations downloaded from the Thomson Reuters Tick History for all tickers included in the S&P500 provided by SIRCA for the period January 1, 2002 to December 31, 2011. The initial download contains 935 tickers.[3] The dataset used in this paper does not purport to be a full history of all stocks on the S&P500, but rather takes the 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). Our process, carefully documented in the Appendix, is programmed in C+. Thus it is possible for researchers to both replicate the data and make their own alterations to the selections. After this process the sample contains 557 stocks.

We are now faced with sample continuity problems. The methodology we propose is best applied to a balanced panel of stocks. To this end 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 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 stock of Fannie Mae and

[3]The SIRCA stocklist '#SP.00' contains many more stocks than actually trade including OTC and alternative exchanges –we retained 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 ticker –there is no unique ticker which traces a single stock through time unlike the unique company or stock numbers found in COMPUSTAT so we match tickers and companies through merger and acquisitions, stock splits and trading halts.

Freddie Mac was 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

The intraday data refers to the last trade in each 5 minute period between 9:30am and 04:00pm each trading day. These 5 minute data are used to calculate annualized daily realized volatilities as the sum of squared intradaily returns, with the overnight returns removed between each day. These realized volatilities form the basic dataset for the article. More precisely, let r_{itj} be the intraday trade return of firm i on day t at 5–minutes time $j = 1, \ldots, J$. The annualized realized volatility is

$$x_{it} = 100\sqrt{252}\sqrt{\sum_{j=1}^{J} r_{itj}^2}.$$

This is the simplest estimator of the integrated volatility from high frequency data and valid if prices follow a Brownian motion. If prices have a jump component this will be incorporated into x_{it}. Barndorff-Nielsen and Shephard (2004) show that in the limit the realized volatility of a Brownian motion process with jumps tends to the sum of the underlying quadratic variation and the squared jumps. While the inclusion of jumps in a measure of integrated volatility is a disadvantage for the analysis that focuses on volatility, in our case is an advantage since x_{it} is a risk measure that embeds information about both the volatility process and jumps. Jumps have been shown to occur in response to information, and to be a distinguishing feature of asset pricing under stressful conditions (Dungey et al., 2009; Lahaye et al., 2011; Andersen et al., 2007; Dungey et al., 2011), 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).[4]

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

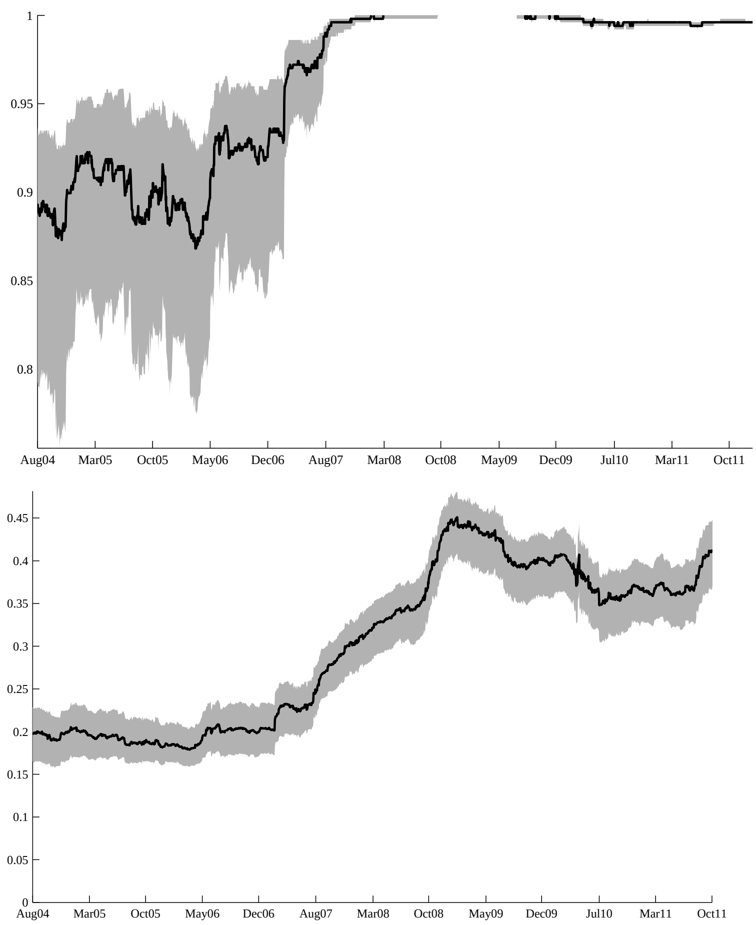
[4] As yet there is no methodology for choosing optimal sampling frequency when working with multiple assets.

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 network

In this section we analyze the interconnection structure of the network in terms of the number of connections and their strength.

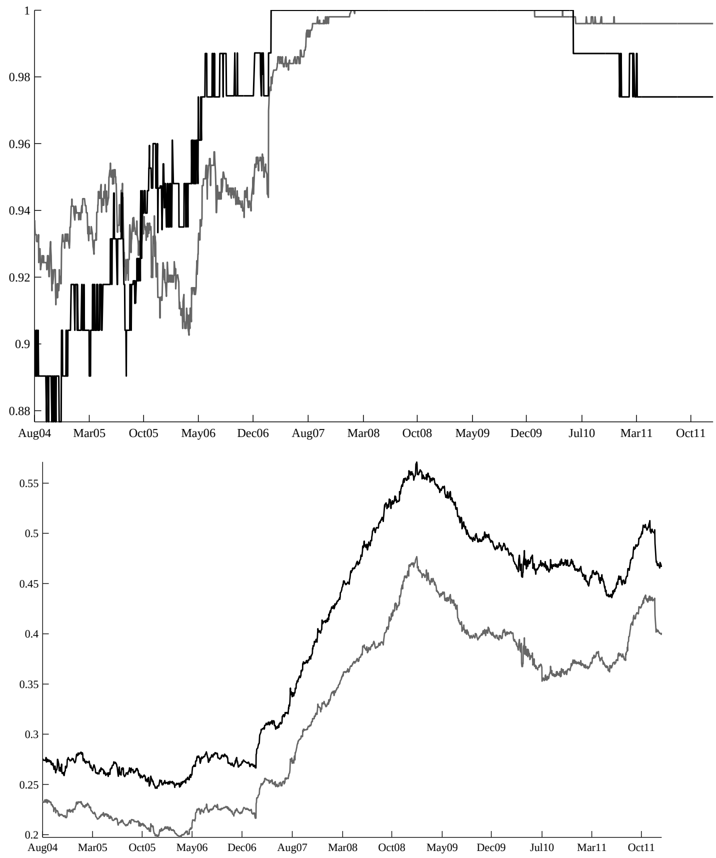
Figure 1: Fraction of connections and their strength – all firms



Upper plot: 50% (solid line), 25% and 75% quantiles (lower and upper limits of the interval) quantiles of the fractions of connections for all firms at each day. Bottom plot: 50% (solid line), 25% and 75% quantiles (lower and upper limits of the interval) quantiles of the correlations for all firms at each moment of time.

The top panel of Figure 1 shows the fraction of companies to which any firm is connected, and the bottom plot shows the strength of these connections. To draw the lines we first measure the median connection and its strength for each company with all the firms of the network. Second, we compute the 50% 25% and 75% quantiles of these medians. The 50% quantile is represented by the solid line while the other two quantiles are used for the interquantile

Figure 2: Fraction of connections and their strength – financials



Upper plot: the black line is the 50% quantile of the fractions of connections between financial firms at each day. At each point in time and for each financial firm we compute the median connection with the other financials. Then we compute the 50% quantile of these medians. The grey line reads similarly but for each financial firm we compute the median connection with all the firms of the system. Bottom plot: the lines read in the same way as in the upper plot but they represent strenghts.

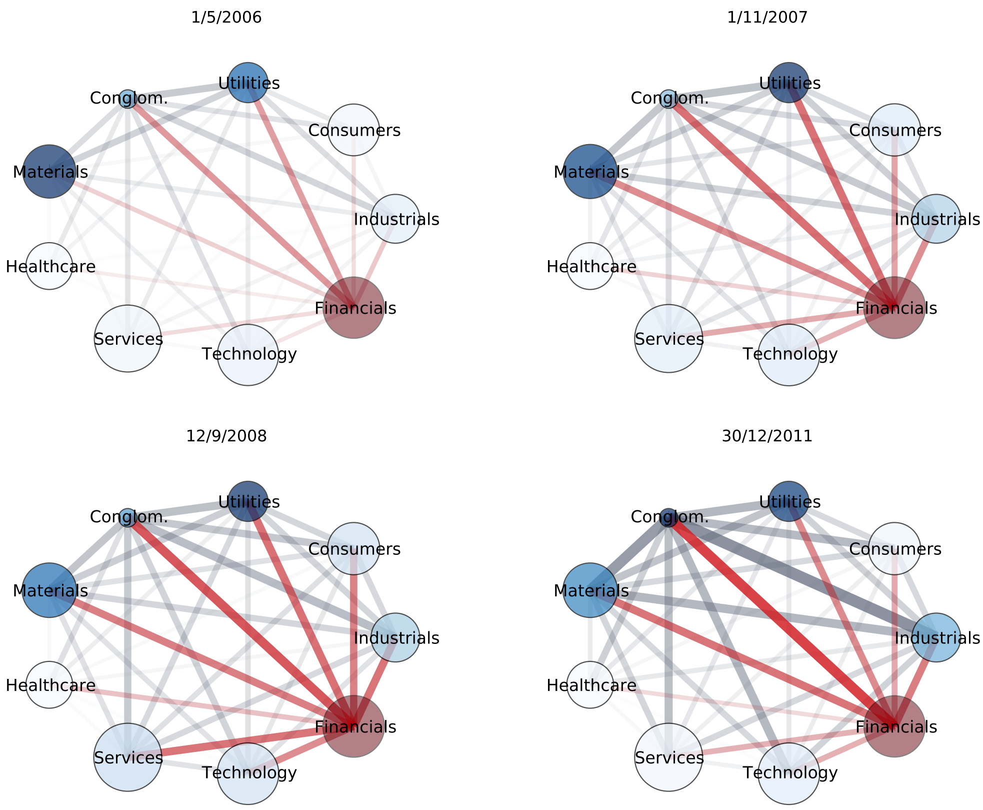
range (grey area), a measure of cross–sectional dispersion at each point in time. Clearly the network connections and their strength have evolved through time. At the beginning of the sample, the strength is relatively small, a 50% quantile around 0.2, and it increases steadily from August 2007 onwards to reach 0.45 at around January 2009. This dovetails with the upper plot, which shows that during the height of the crisis the fraction of connections of the network went to one, i.e. a fully connected network. From August 2007, the network remains almost fully connected with a slight decrease of the strength of the connections that remains in the interval 0.35–0.40 for the rest of the sample.

Figure 2 focuses on financial firms. It reads similarly to Figure 1: the top plot shows the fraction of connections and the bottom plot their strength. The black lines read similarly: we first measure the median connection and strength of each financial company with all the other financial firms and, second, we compute the 50% quantile of these medians. The grey lines read similarly but for each financial company we compute the median connection and strength with all the firms of the system. The conclusions we extract from the upper plot are similar to those in the top plot of Figure 1: the financial firms have always been highly connected, not only within themselves, but also with the rest of the economy. During the pre–crisis build–up the number of connections increased significantly up to a fully connected financial network by early 2007, which then remains in place until virtually the end of the sample. This result dovetails with the strength of connections in the bottom plot. The strength of connections between the financial firms is uniformly higher than their connections within the full system of firms in the economy. From early 2007, the strength of interconnectedness for financial firms alone increased more rapidly than that with the rest of the economy. From 2009 onwards financial firms have maintained a greater degree of interconnectedness within themselves –the difference between the black and grey lines is some 10 percentage points post–2009, compared with a difference between the two of only 5 percentage points pre–crisis. There seems to have been a structural shift in the strength of the interconnectedness as a result of the crisis.

Figure 3 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 (the wider the more connected). A glance to 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 that cannot be ignored.

Figure 3: 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 on the top of the each plots. 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 the sectors are).

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:

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

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, $liq^{-1}_{k\,t}$, 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 $SIFIRank_t$ as the balance sheet data are released every quarter. The choice of α and $\boldsymbol{\omega}$ do not affect calculations of GS_t where $\alpha = 1$. 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 indexes

An index for the financial sector

The plot of the GS_t index (4) is given in Figure 4. 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).

Despite the fact that on September 23, 2008, the S&P500 fell dramatically (by over 400 points), the price of oil rose by a daily record amount and the US dollar fell, our index shows that from September 23, the systemic risk in the financial sector began to decline. This is consistent with the realization of an economic re–adjustment to the ongoing effects of the crisis. At this time Congress was also debating the extent of the proposed $US700 billion bailout funding first mooted by US Treasury Secretary Paulson on September 19. In the event, it was the announcement of the approved TARP, on October 3, 2008, which precipitated a sustained decline in the systemic risk index until the end of March 2010.

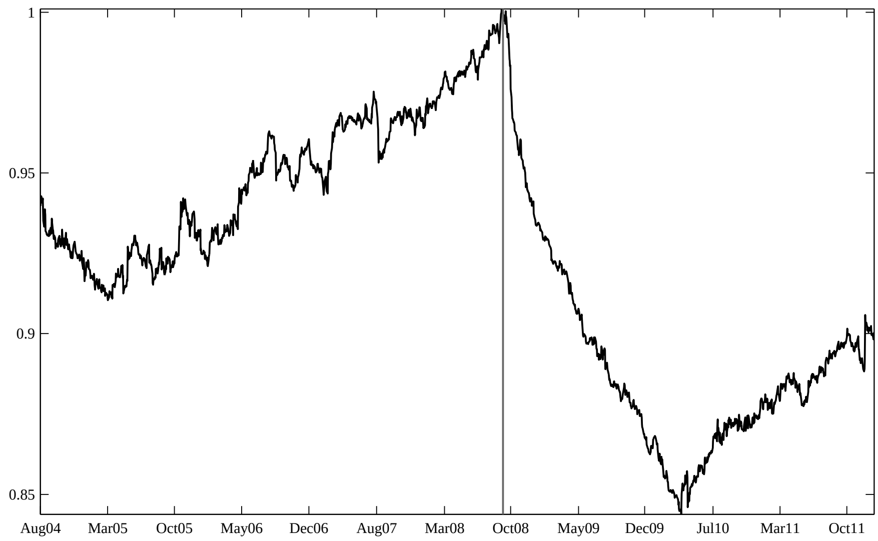
The extent of the fall is sufficient to reduce the index below levels present in the previous four years. This evidence is consistent with that of King (2011) who finds that the announcement of TARP, and its final implementation, significantly reduced the perception of market risk, and more specifically in US banks resulted in a positive shareholder response due to the generosity of the TARP program compared with the conditions imposed in other jurisdictions (for example the UK and The Netherlands). Thus, 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 had improved share market outcomes, although those who did not receive assistance were more strongly rewarded.

The increase in the index from April 2010 aligns with increasing concerns over emerging problems in European sovereign debt markets. 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).

Indices for subsectors

A convenient mean of displaying the results is to adopt the approach of Brownlees and Engle (2011) who divide their sample of US financial institutions into deposit–taking institutions, insurance, dealers and other financial institutions. Our analysis focuses on the 18 deposit–taking institutions and 20 insurance companies of the sample –see Table 1 for the classification. We do not include the 6 companies classified as dealer/brokers due to the difficulties in classifying firms into this category (Brownlees and Engle, 2011) and the small number of firms. Other financial firms are excluded due to the high degree of diversity in their interests; including,

Figure 4: Systemic risk index – financial sector



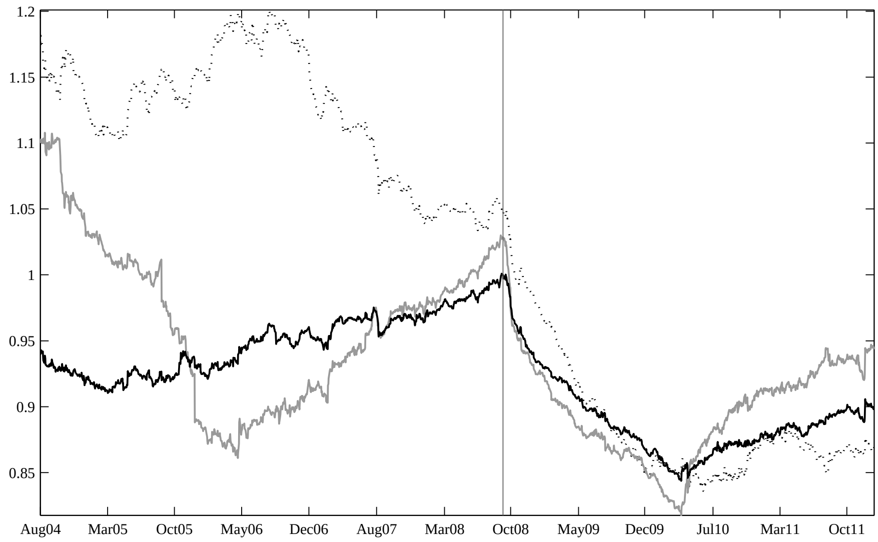
for example, real estate investment, health care investment, and funds management advice.

Table 1: Classification of Financial Stocks

Deposit	**Insurance**
Bank of America Corporation	ACE
BB&T Corporation	AFLAC Inc
The Bank of New York Mellon Corporation	American International Group Inc
Citigroup Inc	Assurant Inc
Comerica Incorporated	The Allstate Corporation
Huntington Bancshares Incorporated	The Chubb Corporation
JPMorgan Chase & Co	Cincinnati Financial Corp
KeyCorp	Genworth Financial Inc
M&T Bank Corporation	Hartford Financial Services Group Inc
Peoples United Financial Inc	Lincoln National Corp
PNC Financial Services Group Inc	Marsh & McLennan Companies Inc
Regions Financial Corp	MBIA Inc
Synovus Financial Corp	MetLife Inc
SunTrust Banks Inc	MGIC
State Street Corp	Principal Financial Group Inc
US Bancorp	Progressive Corp
Wells Fargo & Company	Prudential Financial Inc
Zions Bancorp	Torchmark Corp
	Unum Corporation
	XL Capital

Figure 5 shows the quite distinct differences in the patterns experienced by the deposit–taking institutions (dashed line) and the insurance companies (grey line). For comparison purposes we also show the systemic risk index of the financial sector (black line). The GS index for the depository institutions reached its maximum on August 22, 2006 and its rise is aligned with the rise in housing prices and the subsequent turning point in the US housing market in the second half of 2006 and into 2007. It demonstrates that the index is recognizing the strongly inter–related nature of this aspect of banking sector lending and the increasingly common nature of the vulnerability of the sector's response to shocks. In fact, the values of the index are above 1, reflecting that during the build–up of the crisis, the deposit–taking institutions were considerably more systemically risky that the financial sector as a whole. Once banks were no longer further extending their credit to riskier housing loans their vulnerability began to decline –evidence of reduced activity in this area can be found in the complete lack of new tranches of the ABX index for mortgage backed securities after January 2007; see Dungey et al. (2012). This index declines almost continuously until December 2009, aligned with the problems emerging in Greece, and then remains around those levels until November 2010, when it again begins to kick up.

Figure 5: Systemic risk indexes – financial subsectors

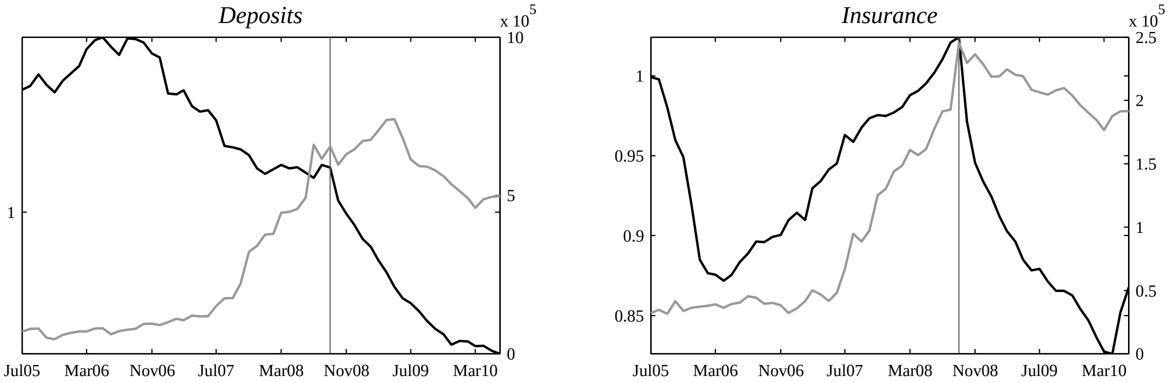


The black line is the GS index for the financial sector, the dashed line for deposit–taking institutions, and the grey line for insurance firms.

The GS index for insurance firms tells a different story. The systemic risk index for these companies rose steadily from May 2006 until September 18, 2008. Clearly the bailout of AIG was a turning point, indicating particularly that their entwinement with all aspects of the economy was critical in systemic stability. This index continues to decline until early April 2010 (April 5) at the point of high market anxiety prior to the scheduled Greek bond sale on April 8 and shows only increasing systemic risk for the remainder of the sample. By December 2011 the insurance companies were more systemic that the financial sector as a whole and, in particular, than the deposit–taking institutions.

There are interesting comparisons between our systemic risk measures and those of Brownlees and Engle (2011). The latter measures risk as potential capital shortfall in the system on a monthly basis, which is quite different from our measure of interconnectedness, although the two are interrelated through spillovers and balance sheet contagion; Kiyotaki and Moore

Figure 6: GS VERSUS BE



The black line is the GS sub–sector index, while the grey line is the BE sub–sector index.

(2002). To compare our results with those of Brownlees and Engle (2011) we construct a monthly average GS index from our daily series, as shown in Figure 6 (left plot for deposit–taking and right plot for insurance firms). Note that the Brownlees and Engle sample ends in June 2010.

A comparison of the GS and BE indices for insurance companies shows that while during the period from early 2005 to September 2008 the systemic risk measured by interconnectedness (GS) was growing, the systemic risk measured by potential capital shortfall (BE) was growing much more dramatically. Both indices turn in September 2008. From then on, the GS index declines relatively rapidly, while the BE index declines more slowly. That is, the capital shortfall measure of systemic risk built steeply prior to September 2008, but this problem was only slightly alleviated during the following period. On the other hand, the systemic risk due to the interconnectedness of the firms declined in a pronounced manner post September 2008, as there was less commonality in the exposure of this sector. Comparing the deposit–taking sector indices shows that although the interconnectedness (GS) measure of systemic risk declined slowly during the lead up to the crisis and thereafter until April 2010, there was a rapid build–up in risk due to potential capital shortfall (BE index), which did not peak until April 2009, two months before the mid–year recession trough according to NBER dating, and by March 2010 was back to levels of May 2008. The BE indices do indicate some kick up in systemic risk in April 2010, tantalizingly aligned with the GS indices increase in response to the emerging European debt crisis.

The importance of macro–financial linkages

Thus far we have provided evidence of the evolution of systemic risk in the US financial sector. The modeling framework, which takes into account the interlinkages between the financial firms with the real economy represented by companies from a wide range of sectors, is justified by the conclusions drawn in Figures 1–3. Now we provide further evidence in terms of the systemic risk indices by studying their behavior if these 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 (sub–)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 7 compares the GS indexes for the deposit–taking and insurance companies constructed with financial and real economy firms (GS_{MFS}) and the index constructed with reference only to financial sector firms (GS_{FS}).[5]

The figures display a distinctive widening of the gap between the GS_{MFS} and GS_{FS} post August 2008. Immediately following this period there is a strong drop in the GS_{MFS} index for both the deposit–taking and insurance sectors, 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.

In the deposit–taking sector, the gap between the GS_{MFS} and GS_{FS} indices begins to open from late 2006, coupling with the turning point in the indices which we have previously associated with the peak of the housing cycle. The slower rate of decline in the GS_{FS} index represents that risk in the deposit–taking sector is declining relative to this sector as a whole (recall that these are the comparator companies in the GS_{FS} index, and that risk in the insurance sector is known to be rising). As the index is relative it is also increased riskiness of other firms that will drive a relative improvement in a single sector systemic risk index. Post the collapse of Lehman Brothers the gap between the GS_{MFS} and GS_{FS} index opens substantially, reflecting a disconnection of the systemic risk driven through these firms with the economy as a whole. This is plausibly linked to the success of the policy interventions around this time, which successfully alleviated the risks associated with financial institutions collapsing through regulatory intervention in an environment where lack of credit was adversely affecting business conditions for the remainder of the economy.[6] Effectively the historical links between the financial sector and the real economy were dramatically reduced for the period post September 2008.

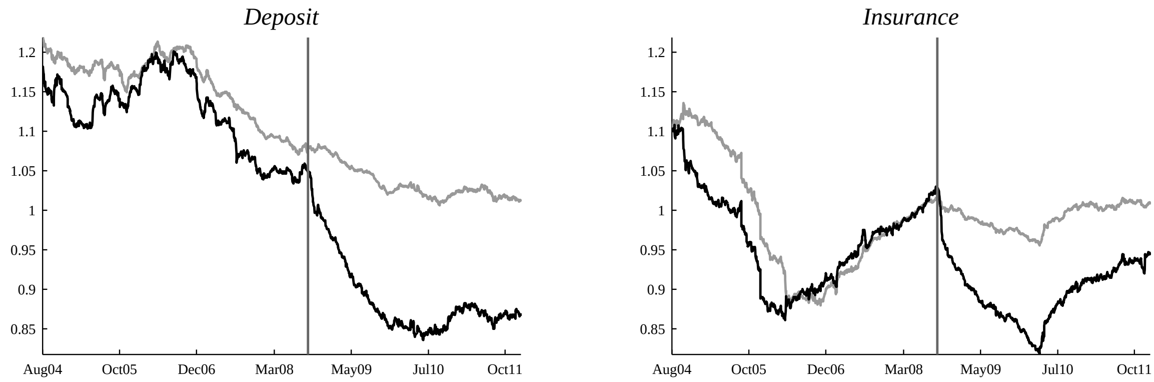
A consistent analysis is evident for the insurance sector. Prior to September 2008, the run–up in systemic risk for the insurance sector measured either relative to the entire sample or to the financial sector alone is equivalent, suggesting that the insurance sector was key in the increasing systemic risk for the financial sector as a whole at that time. Post September 2008, a dramatic gap emerges. The interventions to rescue AIG are particularly evident –the

[5] Comparison of the sector indices is complicated by the normalization of the total GS index. However this does not arise when the sub–sectors are calculated.

[6] Some evidence of this is available in the 35 percent rise in bankruptcy filings in US courts between June 2008 and June 2009 –sourced from US courts statistics available at http://www.uscourts.gov/Statistics/BankruptcyStatistics.aspx.

GS_{MFS} index drops dramatically, although the GS_{FS} index does not. This is particularly compelling evidence that the policy action changed the interconnectedness of risks between the insurance companies and the rest of the economy. While, as a result of credit shortages and declining economic conditions, firms in the real economy became considerably more risky, the insurance companies did not experience the same degree of increase in risk post the AIG rescue. Thus, the GS_{MFS} post–AIG for the insurance companies shows them as becoming relatively less risky compared with the rest of the economy, but the GS_{FS} shows a relatively slower decline in their systemic risk profile. Interestingly, with the end of the US recession in mid-2009 and the beginning of the Greek crisis, the whole economy based index of risk for insurance companies moves towards the financial sector index, recognizing that relative to the rest of the economy, the insurance sector is relatively exposed to market risks in this period. This does not seem to be the case for the deposit–taking firms.

Figure 7: WITH AND WITHOUT REAL ECONOMY LINKAGES



The black line is GS_{MF} 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. Left plot for deposit–taking institutions and right for insurance firms.

5.2 The SIFIRanking

Bucketing SIFIRanking

In this section we analyze the firm–specific results. Since showing detailed results for the 78 financial firms is prohibitive, we opt for the bucketing approach of the Basel Committee on Banking Supervision (2011), BCBS in short, 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 and defined as the equally weighted average of the standardized characteristics divided by the sum of all the bank's scores. BCBS methodology shares certain similarities with ours, such as the standardization of the firm characteristics. But there are also important differences: it does not consider network information but only firm characteristics, it does not consider the linkages with the real economy, and the frequency of the observations is annual.

BCBS assigns the calculated scores 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 by 0.5% for subsequent buckets. This bucketing approach is a convenient way to summarize results; Table 2 shows **SIFIRanking** in four buckets. Each year of the sample 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.

Three main conclusions emerge from the table. First, using their bucketing approach the BIS have identified a list of globally important financial institutions; based on December 2009 information. 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. Based on the **SIFIRanking** bucket results reported in Table 2 we find that all of these institutions consistently appear in our buckets covering the top 30 firms by **SIFIRanking** –that is they are SIFI ranked in the top 30 firms on no less than 80 percent of the days in the sample. In fact, Bank of America, Goldman Sachs, JP Morgan and Wells Fargo are consistently in the top 10, while Citigroup and Morgan Stanley usually rank outside the top 5 (although 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 **SIFIRanking**, and on a number of occasions in the top 5.

Second, Wells Fargo and JP Morgan spend a substantial proportion of the sample period identified as in 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 a much greater presence in the top 5 than it did previously. These three banks suffered the less from the crisis and, in fact, have become bigger and reinforced. 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 present 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

Table 2: Bucketing SIFIRanking

	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			4	2	2	2						
The Allstate Corporation		4		4		4	4	3	3	3	4	4		4
Avalonbay Communities										4				
American Express Company	3	3	4	4	4		4	3	2	1	2	2	4	3
Bank of America Corporation	2	1	2	2	2	1	1	1	1	1	1	1	1	2
BB&T Corporation				3	1	2	1	2	4	4				
Franklin Resources	4			4	3	3	3	3		4	3	3	3	3
Bank of New York	4	3	4	4	4		4	3	1	2	3	3		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	3	4	
Cincinnati Financial Corp	4	4							4	3	3	2	3	3
Comerica	3	3	3	3	3	3	4	4						
Capital One Financial Corp	2	2	3	3										
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	2	3	3
HCP											4	4		
Hartford Financial Services Group	3	3		4	4	3	4	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	4						
Loews Corporation	3								4	3	1	1	2	1
Lehman Brothers	2	2	1	2	1	2	2	2						
Lincoln National Corp						4	3	3					3	3
MetLife	4			4	3	3	2	2				2	3	1
Marsh & McLennan Companies													4	4
Morgan Stanley	2	2	3	3	2	2	2	3	4	4		3	2	2
M&T Bank Corporation		4	2	2	3	3	4	4						
Northern Trust Corporation		4					3	3	2	3	4	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	3	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				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	3						4	4				4	3
T Rowe Price Group		4	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	1	2	1	1	1
Weyerhaeuser Co	3	3	3	3							4	3	4	3
Zions Bancorp			4	4										

This table summarizes **SIFIRanking** by means of the BIS 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. Likewise for 2, 3 and 4.

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, it is worth noting the emerging importance of insurance companies. AIG was in the top 10 (second bucket) companies during the 18 months from July 2007 to December 2008, but they do not reappear after the rescue in 2008. However, by the end of our sample, consistent with the rise in the *GS* index for insurance discussed in the previous section there is a re-emergence of 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. 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. We posit that this represents an increase in risk associated with the Greek debt crisis.

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'.

Interconnectedness and capital shortfall for individual firms

The Stern V–Lab project (accessible at http://vlab.stern.nyu.edu) provides individual systemic risk rankings for financial firms on a monthly basis, ranked using the Brownlees and Engle (2011) method of assessing marginal capital shortfall. We extracted these rankings for comparison with those generated in the previous section for individual firms. As the Vlab project concentrates on individual financial sector firms, we have drawn from the two databases the deposit taking and insurance companies which are covered in both studies.

Figure 8 compares the rankings for the deposit taking institutions. It is readily apparent that many of the deposit–taking institutions rank far higher (that is are indicated as less systemically risky) in the V–Lab rankings than they do in our rankings (which we denote DLV). 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. The V–Lab measure, 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 provides an excellent example. In the first six months of 2007, Citibank's 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. In contrast the SIFI rank of Citibank remained in the top 20 for the entire period.

In fact, a number of the firms in the sample, just like Citibank, showed an abrupt change in their BE ranking around 2007–2008 and have retained heightened risk ranking since then. Bank of America, Comerica, Hungtington Bancshares, KeyCorp, Regions Finanical, Synovus, Sun Trust and Zions are some examples. Others showed a major change in their ranking around the period of late 2008, and then a return to a less risky status, such as Bank of New York Mellon, M&T Bank, US Bancorp, and with some post–crisis abrupt changes Wells Fargo, PNC Financial and Sate Street.

In contrast, the DLV rank shows that a number of the firms which experienced an abrupt change in late 2007 in the V–Lab ranking have showed an improvement in their **SIFIranking** –for example, Citigroup, Keycorp, Regions, Synovus and Zion. Consistent with our earlier analysis for the financial sectors, these institutions are showing sustained risk on capital shortfall measures, but reduced risk via interconnectedness. Only Bank of America shows continued high systemic risk on both measures.[7]

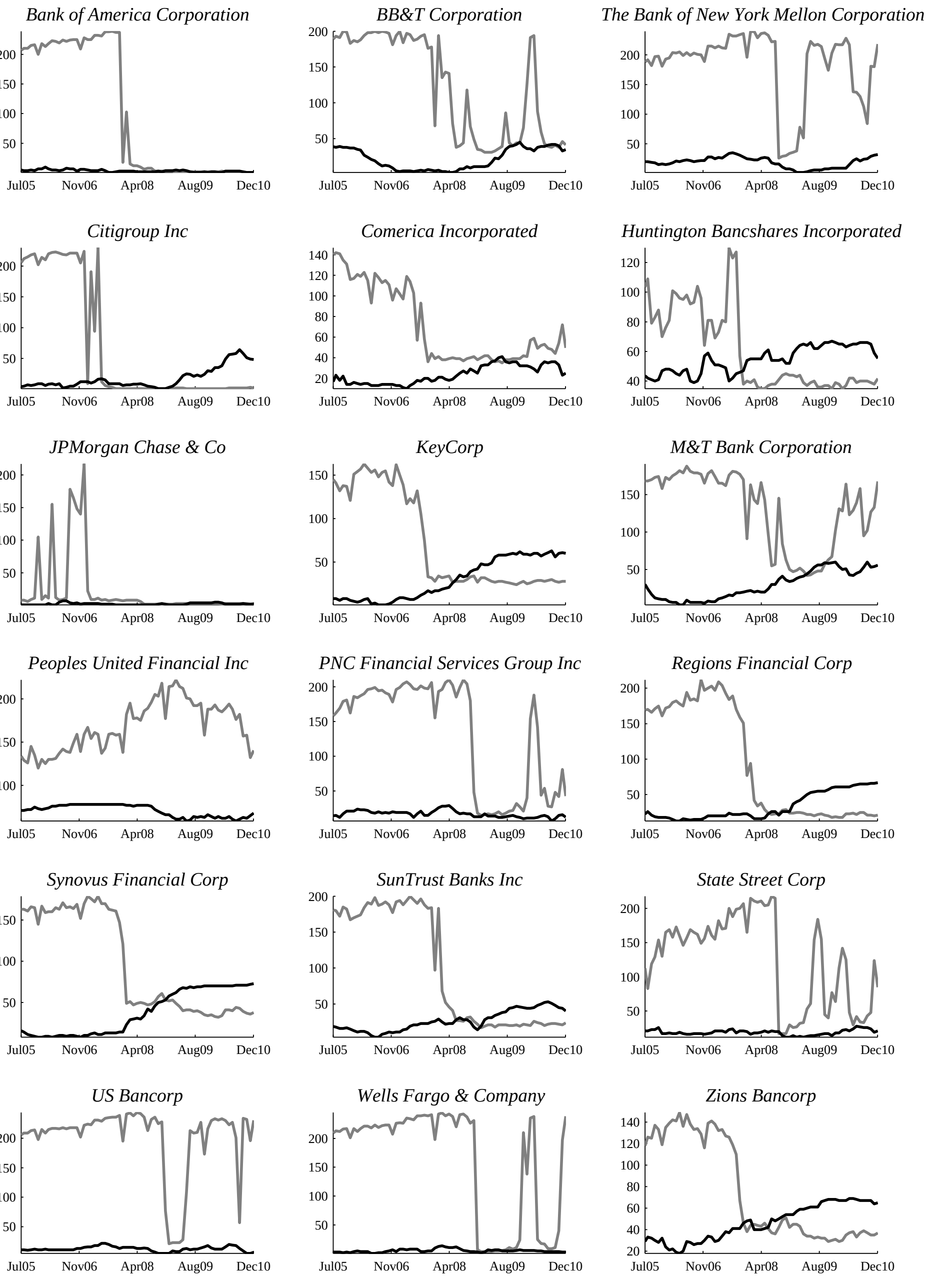
The ranking profiles of insurance companies for the V–Lab capital shortfall measure and the DLV SIFI interconnectedness measure are given in Figure 9. It is apparent the disparity in some of the ranking profiles. In some cases, the V–Lab capital shortfall rank and the DLV interconnectedness rank do not change dramatically over the entire sample, for example Cincinnati, Marsh and McLennan, Principal Financial, Torchmark, and to some extent AFLAC, although the latter is subject to some dramatic variations around early 2009 and late 2011. In other cases, the V–Lab capital shortfall profile has changed little, as in Hartford Financial Services, Lincoln and MetLife but there have been distinct moves in their interconnectedness shown by DLV ranking. For each of these companies their ranking on interconnectedness indicated a drop in risk in the latter part of the sample.

Finally, and arguably most importantly, there are insurance companies who prior to 2007 or 2008 were ranked at 200 or above in terms of capital shortfall risk, and experienced dramatic drops in their index, indicating sudden increases in capital shortfall risk. These include Allstate, Assurant and AFLAC all of whom experienced drops at the time of the AIG crisis. AIG itself, experienced a drop in its capital shortfall ranking earlier, associated with the extra demands for collateral to cover its credit–default swaps and subsequent disclosure in late 2007 and early 2008 of massive unrealized losses (by February 2008 these were in the vicinity of $5.3 billion posted collateral and $11.5 billion unrealized losses). Volatility in the rankings is again visible for these firms; AFLAC shows a dramatic drop and then recovery associated with uncertainty about insurance industry, AllState has a very volatile path through 2009 to 2011 and companies such as Chubb and Marsh and McLennan show spikes which arise due to December reporting effects.

Few of the firms examined above have appeared in the top 10 ranked firms using capital

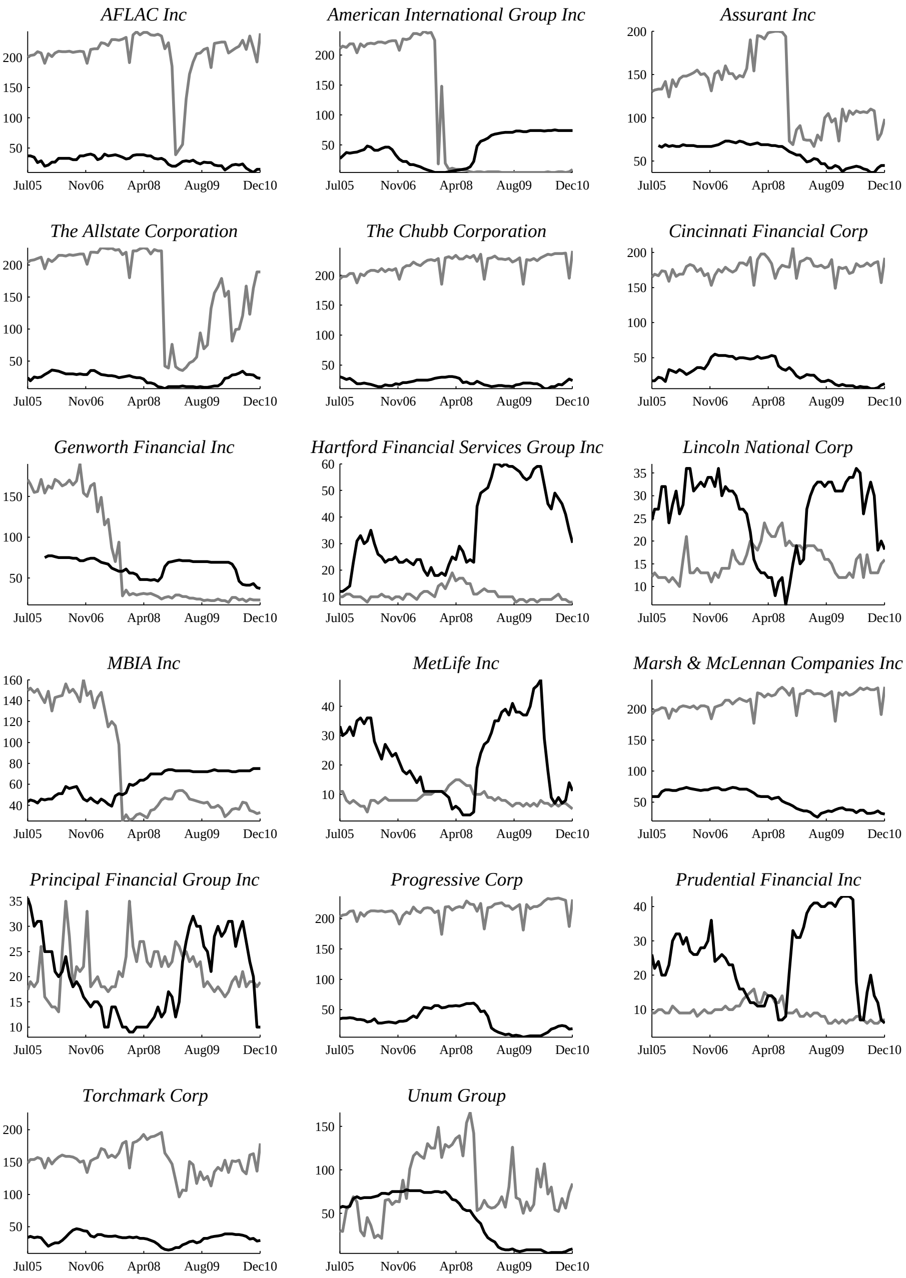
[7] Although Peoples United, and SunTrust both continue to have similar risk profiles on both measures post-crisis.

Figure 8: DLV vs. Vlab – Deposit



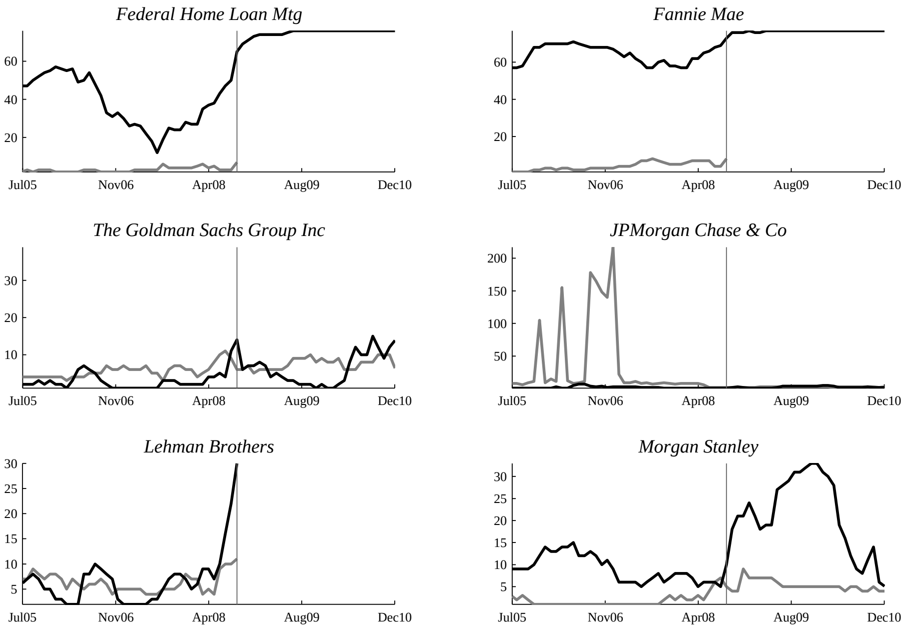
DLV and V–Lab ranking profiles (black and grey lines respectively) of deposit–taking companies.

Figure 9: DLV vs. Vlab – Insurance



DLV and V–Lab ranking profiles (black and grey lines respectively) of insurance companies.

Figure 10: DLV vs V–Lab for top 10 firms pre–crisis



DLV and V–Lab rankings (black and grey lines respectively) for firms that were consistently identified as being in the top 10 of most systemically risky firms in 2005 to 2006 by the V–Lab capital shortfall measure.

shortfall measures prior to the crisis. Figure 10 shows both rankings measures for firms which were consistently identified as being in the top 10 of most systemically risky firms in 2005 or 2006 by the V–Lab capital shortfall measure. There are some notable successes here for both measures. Lehman Brothers is captured in the top 10 in both indices. 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 the V–Lab capital shortfall measure implies. The V–Lab capital shortfall measure, however, clearly identifies the problems with Fannie Mae and Freddie Mac –comparing the two analytical measures emphasizes their complementary nature. The risk with Fannie Mae and Freddie Mac was their severe capital shortfall through high leverage and implicit government guarantee, however they were not as highly interconnected with the remainder of the economy as other financial institutions.

An important facet of the individual comparisons for these risk measures is the at times extreme fluctuations in the V–Lab capital shortfall rankings compared with the relatively smoother path of the DLV interconnectedness **SIFIranking**. This volatility arises due to abrupt changes in balance sheet measures used in the periodic capital shortfall measures, whereas our more continuous, higher frequency observations of market based assessment provide 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 role of firm characteristics

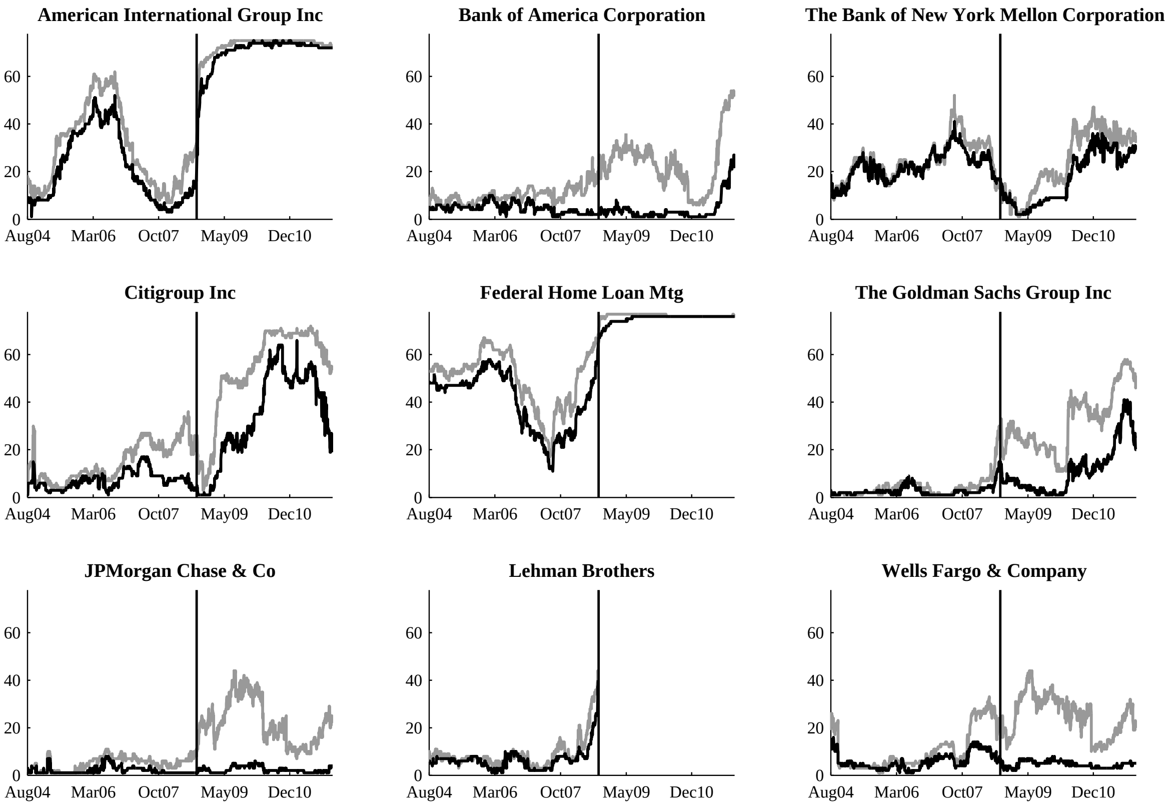
Finally, we examine the impact of including firm characteristics in our assessment of individual firm systemic risk measures. As there are a significant number of firms in our database, we concentrate on those identified in our top 10 percent most frequently identified systemically risky financial companies –Bank of America, Citigroup, Goldman Sachs, JP Morgan, Lehman Brothers and Wells Fargo– and the additional examples of AIG and Freddie Mac as firms which were at the centre of important events during the crisis.

Figure 11 shows the SIFI rank for these individual firms, with (solid line) and without (grey line) taking into account firm characteristics. It is evident that in each case presented here that the systemic rank for each of these important firms in the sample is increased when their firm characteristics are specifically recognized in the network. Note, however, that this is not always the case, and there are examples where firm characteristics make little difference to the systemic rankings; for example Wells Fargo in the early part of the sample, and AIG around the time of its rescue –this latter particularly makes sense as the rescue process is likely to be dominant at this point. Generally, however, for the financial firms which are of greatest interest in this paper, accounting for their linkages and their firm characteristics leads to an increase in the appropriate measure of systemic risk.

6 Conclusions

Trichet's Cambridge lecture ended with the observations that macroeconomic policy interventions had had a stabilizing effect. In this paper we have shown the importance of including the interactions between the real economy and the financial sector in assessing the systemic risk of the financial sector in the US. It is clear that widening the scope of our network to include non–financial firms alters our understanding of the importance of the financial firms –in some important periods, such as following the recent crisis, the real economy acts to mitigate risks. However, our analysis is confined to one economy, albeit the largest and most important financial centre. It would not be at all surprising if further insights could be garnered from examining domestic and international networks, particularly given the international nature of many of the most systemic banks identified in our study. Cerutti et al. (2012) promote the importance of international linkages amongst the banking sector –and it seems likely that further linking the financial sector to the real economy would enhance these results. Building such an enhanced network is scope for further work.

Figure 11: The role of firm characteristics



Sensitivity of **SIFIRanking** to firm characteristics. The grey line is without them, while the black line includes the firm characteristics in $\mathbf{S}_t$.

Acknowledgements

This work was written while David Veredas visited the Department of Monetary and Financial Studies at the Banco de España (Madrid, Spain). We are grateful to Christian Brownlees and Bernd Schwaab for sharing their results for comparison purposes, and to Torben Andersen, Stefano Battiston, Christian Gourieroux, Graciela Kaminsky, Andrew Lo and André Sapir for useful remarks. We also thank SIRCA for assistance with extracting the high frequency data used here and Thomson Reuters Datastream as data provider of the firm characteristics as well as Benoit Dewaele and Sharon Raymond for assistance. We acknowledge exceptional research assistance from Jet Holloway. We are also grateful to Tarik Roukny Ornia for assisting us with the network plots, and to the seminar and conference participants at the Banco de España, the FOC and CRISIS School on Complex Financial Networks (IMT, Italy), the Latsis Symposium 2012, the 5th International Conference on Computational and Financial Econometrics (CFE'11), and the Universities of Georgetown, libre de Bruxelles, Pompeu Fabra, Princeton. Matteo Luciani is *Chargé de recherches* F.R.S.–F.N.R.S. and gratefully acknowledges their financial support.

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