Systemic risk in the US: Interconnectedness as a circuit breaker

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ABSTRACT

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

1. Introduction

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

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

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

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

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

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

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

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

Second, we compare our *GS* index with the index of Brownlees and Engle (2017), which is based on potential capital shortfall. Both measures indicated growing systemic risk in the lead up to September 2008. However, following the policy intervention of TARP interconnectedness risk falls, but systemic risk measured by capital shortfall does not, meaning that policies of this nature can act as a circuit breaker in agitating the crisis effects via the real economy; see also evidence in King (2011).

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

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

2. Methodology

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

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

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

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

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

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

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

The shocks in risk are computed by filtering the daily realized volatilites with ARFIMA models (see Section 3 for more details).

The system of systemic importances can be written in matrix form as $\mathbf{S}_t = \mathbf{C}_t \cdot \mathbf{S}_t$. The matrix $\mathbf{C}_t$ plays the role of the hyperlink matrix in network design, where element ij is non-zero when there is a link from node j to node i (where nodes in this case are individual firms). Every column of the hyperlink matrix sums to one – as long as that firm is connected to at least one other firm in the system. The solution is the eigenvector associated with the largest eigenvalue of $\mathbf{C}_t$, which by construction is one.[3]

One of the features of the build-up of the financial crisis was the increase in system-wide risks, which is captured by the average systemic importance of the financial sector. Indeed, as the strength of the transmission channels increases, the network becomes more dense, which translates into an increase of the systemic importances. Let n be the number of financial firms in our system and, without loss of generality, let us assume that the financial firms are order first so that firm $k = 1, \ldots, n$ is a financial firm, and firm $k = n + 1, \ldots, N$ is a non-financial firm. Then, the systemic risk index of the financial sector, denoted GS_t, equals

$$GS_t = \sum_{k=1}^{n} \frac{S_{kt}}{n}. \tag{3}$$

Finally, our ranking metric –the Systemic Risk (SR) ranking– is

$$SR_t = \text{rank}(\mathbf{S}_t). \tag{4}$$

The construction of the system also allows us to construct subsector indices; S_t is a matrix of systemic risks of both financial and non-financial firms. To illustrate the influence of the linkages between the insurance sector and the real economy we construct a financial (sub–)sector index, denoted $\widetilde{GS}_t$, which uses only the set of firms in the financial sector as the base for calculating the measures, i.e. the systemic importance of firm k at time t as it is defined in (1) is replaced by $\widetilde{S}_{kt} = \sum_{j=1}^{n} \widetilde{S}_{jt} c_{kjt}$ which only contains information about the connections between financials.

The methodology we propose is straightforward and quick to calculate with no need for optimizations, and it takes into account linkages between the financial sector and the real economy. This apparent simplicity belies its demonstrated effectiveness; see the analysis in van de Leur et al. (2017).

2.1. Constructing confidence bands

There exist a number of possible avenues to generate confidence bands, and *a priori* it is difficult to discriminate between them. A first possibility is to bootstrap the risks shocks, and then use the bootstrapped shocks to generate bootstrap realized volatilities. Once the bootstrapped volatilities are generate we can repeat the whole procedure of calculating the systemic risk index.

A second more tractable possibility consists of bootstrapping the risks shock, and use the bootstrapped shocks to compute directly the correlation coefficients ρ_{kjt} in Equation (2). Finally, a third possibility is to skip the bootstrap, and to simulate at each draw d the correlation coefficients. For computational tractability we implement this third avenue (noting that this system is relatively large with over 500 firms involved).

To simulate the correlation coefficients we exploit the approximate distribution of the Fisher transform of the correlation coefficient. Namely, let $\hat{\rho}_{kjt}$ be the correlation coefficient between the shocks of

asset k, and the shocks of asset j, estimated on the sample ending at time t; and let

$$\hat{z}_{kjt} = \frac{1}{T} \log \left(\frac{1 + \hat{\rho}_{kjt}}{1 - \hat{\rho}_{kjt}} \right)$$

be the Fisher transform of $\hat{\rho}_{kjt}$, which is approximately normal with mean $\hat{z}_{kjt}$ and standard error $\frac{1}{\sqrt{T-3}}$. Then at each draw d we simulate $z_{kjt}^d \sim \mathcal{N}\left(\hat{z}_{kjt}, \frac{1}{T-3} \right)$, and we apply the inverse Fisher transform to get ρ_{kjt}^d, namely[4]:

$$\rho_{kjt}^d = \frac{\exp\left(2z_{kjt}^d \right) - 1}{\exp\left(2z_{kjt}^d \right) + 1}.$$

At each draw the algorithm works as follows: ρ_{kjt}^d is generated as explained above, (ii) c_{kjt} is computed as in (2), (iii) $\mathbf{S}_t^d$ is computed as the eigenvector associated to the largest eigenvalue of $\mathbf{C}_t^d$, and (iv) the GS_t^d index and the ranking SR_t^d are computed using (3) and (4). For each window this procedure is repeated 500 times, which gives a distribution for the index of systemic importance, and the ranking.

A crucial issue when simulating correlation coefficients is how to treat those entries that are not statistically different from zero. There exists a large statistical literature (see Bickel and Levina, 2008; Fan et al., 2013; Lam and Fan, 2009; among others) that has studied how to estimate large covariance matrices, and the proposed estimators always include some thresholding technique, which in our case is the testing procedure. Some of these thresholding techniques have the so-called "oracle property", meaning that they consistently set to zero those correlation coefficients that are indeed zero. When a given thresholding technique has the oracle property, then the correct approach is not to simulate those entries that are cut out by the threshold. On the basis of this, in our simulations we set $\rho_{kjt}^d = 0$ if $\hat{\rho}_{kjt}$ is not statistically significant, and when $\hat{\rho}_{kjt} \neq 0$, we simulate ρ_{kjt}^d as described above.

In summary, our confidence bands measure uncertainty on the strength of the connections, not uncertainty on which connections really exist. Thus, the procedure we adopt is an approximation. The issue of estimating large covariance matrices, and of constructing the relative confidence bands, is a focus of current attention in the statistical literature and it is outside the scope of this article.

3. The great financial crisis, and beyond

Results are based on a newly compiled high frequency data set on high frequency returns in the component stocks from the S&P500 index. The dataset is composed of 502 time series, from January 2, 2003 to December 30, 2011, for a total of 2262 trading days. For each firm in the network, the shocks are calculated as the unexpected daily realized volatilities, i.e. the difference between the estimated realized volatility and its expectation. Our measures of the expected realized volatilities are computed with ARFIMA models,[5] while the realized volatilities are estimated simply by summing the squared intraday returns over the day.[6] Our choice of realized volatilities rather than returns as the items of interest represents the generally greater interest in volatility transmission as a measure of shocks or uncertainty during periods of stress.

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[4] For details on the Fisher transformation see Stuart and Ord (1994) volume 1.

[5] This choice is motivated by Andersen et al. (2001, 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.

[6] The details on the intraday returns dataset and on how we compute the realized volatilities are explained in the Appendix.

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[3] The transmission matrix $\mathbf{C}_t$ has zeros in the main diagonal, since a firm does not transmit risk to itself.
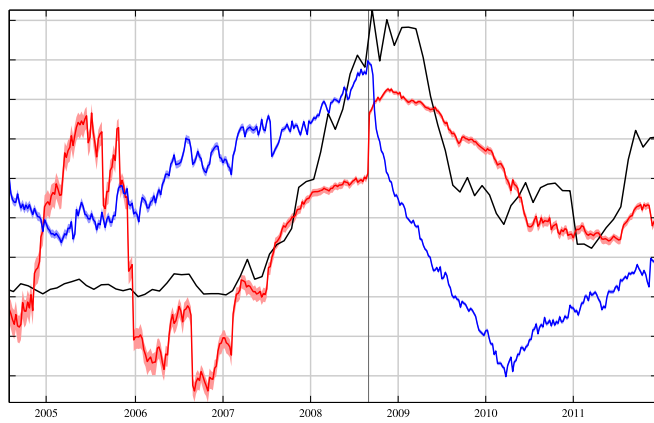
The blue line represent the GS_t index defined in equation (3), while the shaded area is the 95% confidence bands. The red line represents the $\widetilde{GS}_t$ index for the financial sector with shaded area representing confidence bands. The black line is the $SRISK$ index. The vertical black line indicates September 15 2008, the day in which Lehman Brothers filed for Chapter 11 bankruptcy protection. Note that the two indices are standardized to be mean zero and variance one for comparison purposes, which is why there is no unit of measure on the y-axis.

Fig. 1. Systemic risk index for the US economy.

The time-varying analysis is computed with a rolling window of 400 days (roughly 1.5 years). The first window starts in January 2003 and ends in August 2004, meaning that the results cover from August 2004 onwards. Every time the window is rolled, the shocks and the correlations between them are computed, and each correlation coefficient is tested against the null $\rho_{jkt} = 0$. The test used exploits the approximate distribution of the Fisher transform of the correlation coefficients (see for example Stuart and Ord, 1994). This procedure is repeated once a week on the last day of the week (meaning on Friday unless the market was closed).

Interpretation of systemic risk index movements has the advantage of being relatively straightforward. An increase in the index occurs when firms behave similarly, so an increase in $\widetilde{GS}_t$ indicates when financial firms are commonly experiencing increased unexpected volatility. This situation is akin to what is represented in most systemic risk indices, where focus is on the financial sector alone. However, $\widetilde{GS}_t$ also takes into account how indirect linkages with non-financial firms affects these relationships. On the other hand, increases in GS indicate situations when both financial and non-financial firms are moving in the same direction. That is, shocks in volatilities move in the same way across a wide variety of sectors. This is potentially the most systemically threatening outcome for an economy, as it is consistent with increased uncertainty or risk taking across a wide range of industries. Key to this insight is that it does not matter whether firms are making profits or losses as the system will be exposed to increased risk when companies move in a similar direction due to a lack of diversification. When indices for sectors and/or companies diverge, this provides evidence of possible diversification benefits available in the market.

The plot of the GS_t index (3) is shown in blue in Fig. 1. The figure clearly reaches its peak on the day deemed most risky in the sample – which in this case is September 11, 2008. It shows a general increase in systemic risk evident over the pre-crisis sample, and a rapid decline thereafter.

The financial sector systemic risk $\widetilde{GS}_t$ is shown in red in Fig. 1, and is more complex than the overall index. Five sub-periods are clearly evident. Period I up until early 2006 presents a time of plenty - there

is a general buoyancy in the markets and good profits are common. However, in 2006, in line with the pause (and subsequent decline) in the quantity of housing market lending some banks begin to restrict credit. The economy is still experiencing good growth, but borrowing is a little more restricted - this period is evident in 2006–2007. In the period from 2007 until the advent of the crisis is the period we denote the credit risk transfer period. The banks have reduced their lending for housing, and a number of financial firms (such as the Bear-Stearns hedge fund) begin to feel the pinch. There is a collapse in the prices and issuance of Asset backed securities, evident in the ABX indices; see Dungey et al. (2013).

The crisis is associated with a peak of tensions for the whole economy but less so for the financial sector itself (due to the offloading of the risky exposures via credit risk transfer). Ultimately the bankruptcy of Lehman Bros followed a week of growing stress in the financial system which included the Federal takeover of Fannie Mae and Freddie Mac and a period of intense speculation as to whether regulatory intervention would occur to save Lehman. This is evident in the rapid increase of the $\widetilde{GS}_t$ index at the peak of the crisis in September 2008. 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 2011.

From September 23, 2008 our index shows that the systemic risk in the financial sector began to decline. This is Period IV in our analysis, where 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. The index for systemic risk GS fell sharply with the rescue of AIG and the announcement of TARP. However, the fall in the index focused only on financial firms, $\widetilde{GS}_t$, took longer to decline, consistent with the problems noted in the rest of the literature in the banking sector – as these programs did not address the capitalisation problems in the banks. The period where both indices are declining is our Period IV.

In Fig. 1 we compare the GS index with the monthly $SRISK$ index of Brownlees and Engle (2017). The index of Brownlees and Engle (2017) measures risk as potential capital shortfall in the system, which is quite different from our measure of interconnectedness. However, the two measures are highly complementary. One gives information about the interconnected nature of the economy, and the other gives information about the capacity of the economy to absorb a financially traumatic shock. Immediately after September 2008 the drop in interconnectedness represents the brake applied by policy interventions to the downward spiral between financial and non-financial firms, whereas the continued high level of $SRISK$ and $\widetilde{GS}_t$ captures the continued problems with recapitalising the banks. When both GS and $SRISK$ are rising the danger from a systemic event is high as it is likely to both spread widely and be highly disruptive to the capitalisation of the economy.

Given that we know that the financial firms are behaving more similarly (from $\widetilde{GS}_t$) we infer that the diversity evident from GS occurs because there has been a breaking of the link between financial firms and real economy firms. Although financial firms may still be under considerable stress, evident in the continued stress evident after the Lehman Bros collapse in indices such as $SRISK$ in 2017. We infer that the diversity evident from GS occurs because there has been a breaking of the link between financial firms and real economy firms.

A reduction in systemic risk due to the TARP announcement is consistent with evidence of reduced perceptions of market risk and the generosity of the program, compared with those implemented in European and British jurisdictions, see King (2011). In response to the res-

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

cue 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.

The behavior of the financial sector index and the overall index is markedly different after 2010, Period V. Here $\widetilde{GS}_t$ stabilises while GS begins to rise again, reflecting that the financial sector firms are somewhat stable in their relationships with each other, while the differences between financial sector and real economy firms is reducing (there is increased correlation). Systemic risk begins to increase again for the overall index 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).

To sum up, 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.

4. Deposit-takers and insurers

The data set contains 20 insurance companies and 18 deposit–taking institutions (all of whom were recipients of funding from TARP); see Table 1 for the classification. We do not concentrate on the separate indices for other financial firms in the data set due to the diversity of their interests, for example, dealer/brokers, real estate investment, health care investment, and funds management advice.

Fig. 2 provides a scatterplot of the average of the *SR* ranking for each of the 502 firms in the system by year, for an individual firm (horizontal axis) against the standard deviation of its ranking (vertical axis). The open circles represent the non-financial firms, blue xs are banks, red squares are insurance firms, and black asterisks are other financials.

There are two areas of the curve described by the scatterplot that are likely to be of interest to regulators. The first is the area of firms at the left end of the curve. These firms are consistently ranked amongst the most systemic – and they do not often fall out of this category. Across the years spanned by our sample closest to the origin we generally find four banks: JP Morgan, Wells Fargo, Bank of America, and Lehman Brothers. Of these, 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 Federal Deposit Insurance Corporation (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 the curve described by the scatterplot. 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. Firms at the far right hand end of the plots are unlikely to be of interest to policy makers, they are consistently not very systemic.

In 2005, 2006 there were around 10 financial institutions in the far left corner of the scatter plots, including those already mentioned above. This built dramatically in 2007. 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 also is an elevated number of financial firms showing systemic risk. From 2009 onwards the situation changes with a dramatic drop in the number of financial firms in the far left corner, and even fewer 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 and Prudential make
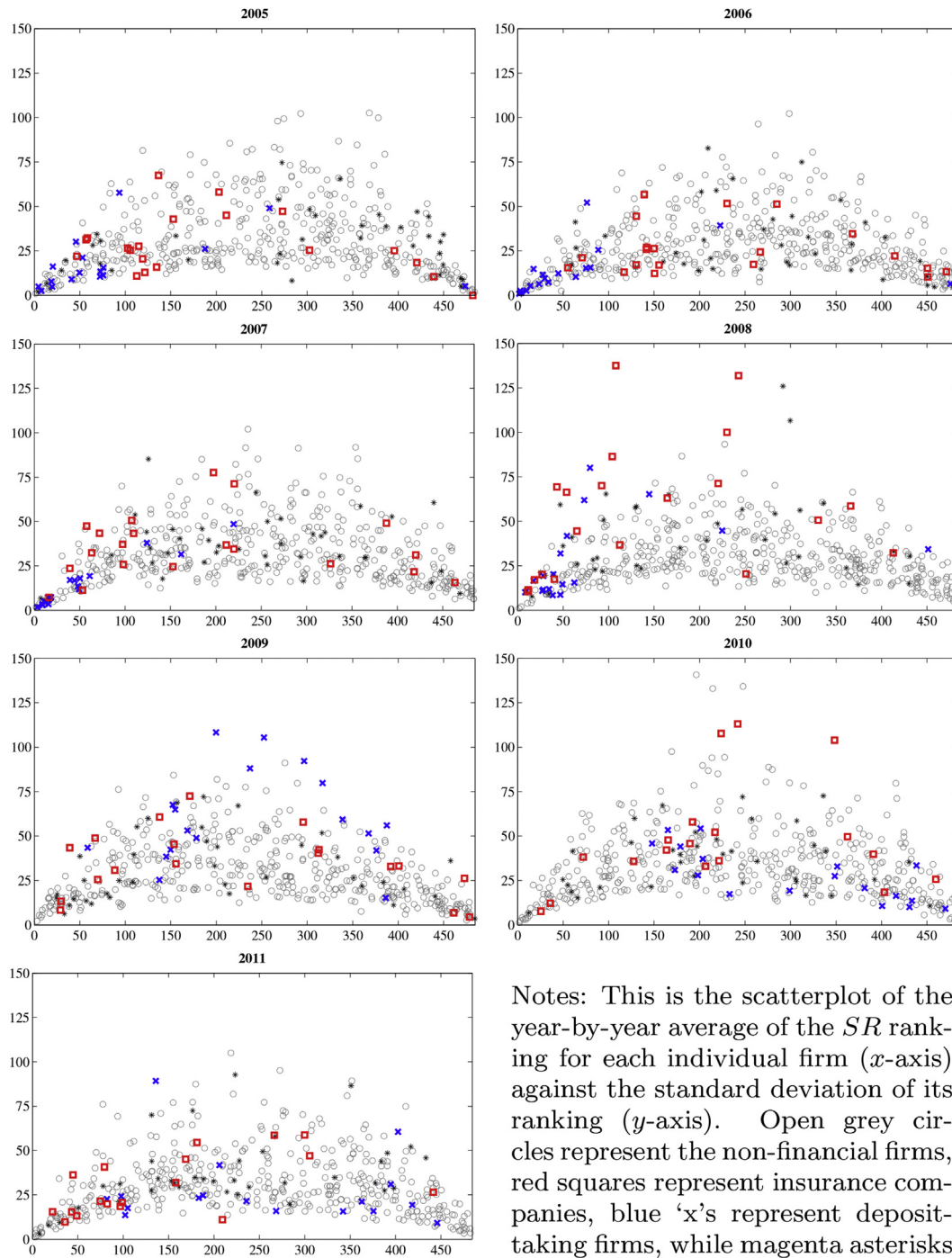
Notes: This is the scatterplot of the year-by-year average of the SR ranking for each individual firm (x-axis) against the standard deviation of its ranking (y-axis). Open grey circles represent the non-financial firms, red squares represent insurance companies, blue 'x's represent deposit-taking firms, while magenta asterisks represent other financial sector firms.

Fig. 2. Mean versus standard deviation rankings by year.

an appearance in this category in the last two years of our sample.[7]

In all, these plots provide an easily digested visualisation of the systemically important financial institutions drawing from the daily SR ranking computed from a system of interconnected risks amongst the real and financial sectors in the US. They summarizes the analysis of

the changing nature of the links between companies 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 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.

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[7] 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.

4.1. Insurers

The spread of regulatory attention to insurers since the rescue of AIG prompted protests from the industry, and reassurance from policy makers that insurers are recognized as less systemically risky than the banking sector. The results provide empirical evidence using a scatter plot (Fig. 2) of the average ranking of individual firms on the horizontal axis against the standard deviation of that ranking on the vertical axis. The **x** show the location of the deposit-taking firms, while squares show the insurers. Other financial sector firms are given by asterisks. It is immediately apparent that not only there are a substantial number of systemically important financial firms near the origin, but that there is a distinct pattern in the location of banks and insurers that contributes immediately to the policy debate. Of the most systemically important financial firms, the deposit taking and other financial firms are nearest the origin – that is they are consistently the most systemic. This group includes JPMorgan Chase, Lehman Brothers, Bank of America, Wells Fargo, Goldman Sachs, US Bancorp, Morgan Stanley, and PNC Financial Services Group.[8] Insurers comprise a broad second group, concentrated – with Principal Financial, Loews, MetLife, Prudential, and Allstate clustering together. This is entirely consistent with the existing rhetoric from both the discussion and empirical evidence of the academic literature, regulators and the industry that insurance is not as systemically important as banking.

A different pattern emerges near the apex of each plot. Firms in these positions can move quite considerably. If we undertake a scatterplot for the entire sample period we find that the firms nearest the apex (and their co-ordinates) are AIG (238,201), Synovus (211,202), Unum (235,178), that is two insurers – AIG and Unum – and a community bank.

The case of Unum is cloudier than most, as it is considerably complicated by a significant settlement package in May 2008 around allegations of artificially inflating stock prices during the early part of the decade. This couples with a number of significant settlements regarding bad faith practices in insurance payouts and company rebranding from UnumProvidential to Unum in 2007 to make this a particularly difficult firm to characterize.

The path of Synovus reflects their rapid decline from a record profit year in 2006, accompanied by ambitious geographical expansion plans to a group with a goodwill impairment of $480million in 2008, badly affected by the decline in the housing market in its regional homeland in the South Eastern States and making financial losses every year from 2008 to 2011 (Synovus Annual Reports, 2006–2012). Synovus had sufficiently impaired capital that it undertook a $968 million TARP contract with the US Treasury, and had a substantially longer period until repayment in July 2013 than most institutions.[9] As part of its return to profitability in 2012 it has undergone a dramatic restructure, consolidating its previous 30 banking charters into one organization, but attempting to carefully retain its image as a community based bank.

The AIG case has been subject to detailed analysis – Harrington (2009) provides an excellent review – particularly detailing the complex nature of this conglomerate of over 70 companies in 2006, their high exposure to the CDS market, mortgages, securities lending, and the extent to which their fate was interwoven with that of the banking sector. Harrington (2009) makes a convincing case that the rescue of this company was critically affected by considerations of their counter-

Table 2
Position of AIG in scatterplot by year.

Year	Average rank	Standard deviation
2005	137	68
2006	285	52
2007	58	48
2008	108	138
2009	473	27
2010	496	1
2011	494	5

party relationships. Many banking sector firms would have been seriously affected by failure of AIG – and this extended well beyond simple US counter-parties, the EU banking system was highly vulnerable to any potential collapse in AIG.

The details of how AIG has fared in a year by year analysis is provided in Table 2. In 2005, 2006 it is apparent that it was ranked relatively towards the right hand end of the scatter, although still with reasonably high standard deviation, and that in 2007 it dramatically increased in systemic riskiness to be ranked 48th that year - in 2008 this receded to an average of 108th ranking but in 2009 ricocheted back to a rank of over 400, reflecting the effects of the calmer market concerns about AIG after the rescue plan was enacted.
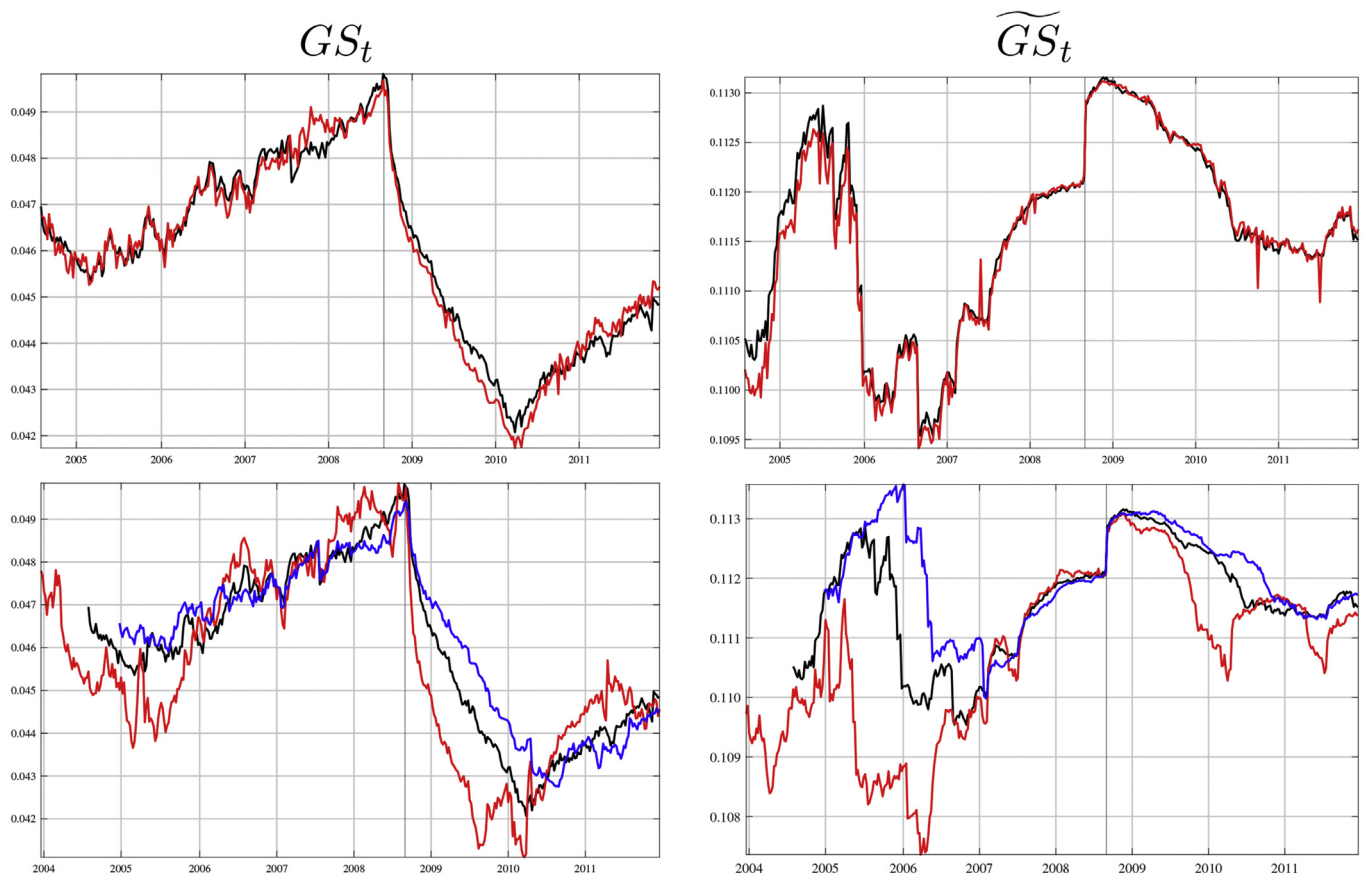
A number of other institutions, such as Zions and Marsh and McLennan, have an average ranking around the middle of the horizontal axis but with lower standard deviation – although this must be placed in context that the standard deviation remains considerably above that of the majority of real sector firms. Other institutions which fluctuate considerably across the time span are Freddie Mac, which, along with Fannie Mae, was taken into conservatorship on September 6, 2008 before returning to government sponsored enterprise status - Fannie Mae on the other hand may be found to the right of the distribution at coordinates. The firms of no regulatory interest, that is those in the extreme right of the scatterplot, are typically not from the financial sector, although one deposit taking institution, the People's United Financial is in the consistently least systematically important group.

The results support the industry and regulatory claims that insurance companies are less systemically important than the banking sector. However, as an industry group, the insurance companies are clustered immediately behind the banking sector in the systemic threat they pose to the economy. This comes about due to the strong interlinkages both within the financial sector, between banking and insurance, see also Schwarcz and Schwarcz (2014), but also through their strong links to the real economy – both through the insurance services they provide and their ventures into non-traditional risk taking products.

If macro-prudential regulation is designed to limit the disruptions to the real economy caused by withdrawal and contraction in credit markets, then the growing presence of insurers in this market argues strongly for their inclusion in a regulatory framework which recognises the differential nature of their underlying customer base, whereby runs on insurance policies are unlikely although catastrophic events challenge capital periodically. The challenge will be to avoid regulatory arbitrage emerging in another sector of the economy to exploit the highly profitable business of the credit risk transfer services which are highly valued by the non-financial consumer and producer sectors of the economy.

4.2. Robustness

Here we record the robustness of the results to the data pre-filtering method and the choice of window length. The top panels of Fig. 3 show the robustness of the results to use of an ARMA(1,1) pre-filter for the stock data in contrast with the ARFIMA results presented in the body

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[8] American Express Company, The Goldman Sachs Group Inc, Lehman Brothers, and Morgan Stanley are (or were) non deposit taking financial institutions, hence its classification on the asterisk group.

[9] Extensions of TARP liabilities beyond December 2013 attract a higher rate of return to the Treasury.

$$GS_t \qquad \widetilde{GS_t}$$

The left column shows robustness analysis for the GS_t index defined in equation (3), while the right column show robustness analysis for the $\widetilde{GS_t}$ index for the financial sector. The upper plots show robustness analysis with respect to the model used to compute the volatility shocks. The black line is obtained by estimating an ARFIMA model (benchmark model), while the red line is obtained by estimating an ARMA(1,1) model. The lower plots length of the window used to estimate the model. The black line uses a window of 400 days (benchmark model), the red line is obtained by using a window of 250 days, and the blue line a window of 500 days. In all plots, the vertical black line indicates September 15 2008, the day in which Lehman Brothers filed for Chapter 11 bankruptcy protection.

Fig. 3. Robustness to filtering and window length choices.

of the paper.[10] The left hand panel is the overall index and the right hand panel the financial sector index. It is immediately evident that the two lines (the black with ARFIMA pre-filtering and the red with ARMA pre-filtering) are substantially the same. The lower panels of Fig. 3 show the overall and financial systemic risk indices produced using moving windows of 250 days (red), 400 days (black) and 500 days (blue). It is apparent, particularly for the overall index that these make little difference with the exception of the usual result of smaller moving windows being associated with greater volatility and earlier detection of change, whereas longer windows are associated with less volatility and later detection of change. The earlier detection of change

and greater volatility of the smaller window is most apparent in the financial sector index, where it records a much earlier and larger drop in systemic risk in 2005 than the drop recorded in the long window index in 2006. Reassuringly, however, all three indices move simultaneously sharply upwards in September 2008, representing their ability to detect rapid dramatic changes in systemic risk.

5. Implications

The *GS* index, and the associated analysis of the relationship between its mean and standard deviation over time, reveal two strong empirical messages for policy makers. First, the relationships between financial sector and real economy firms are vitally important in understanding the role of policy interventions to protect the economy during periods of crisis. Although interventions such as TARP have not been noted as reducing systemic risk assessed via capital loss measures

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[10] An ARIMA pre-filter would imply non-stationary realized variance, and is hence not considered.

such as SRISK, they do make a considerable difference to the interconnectedness between the financial and real economy sectors. By separating these two sectors the intervention acts to dampen the feedback effects between them. In this way the real economy is somewhat protected from lack of credit to continue operations, and subsequently protects the financial sector from further loss due to bankruptcy and business failures in the real economy. Interventions to reduce connectivity clearly have a place in the policy makers arsenal if the goal is to minimize the overall loss of economic activity during a financial crisis. This of course, does not mean that the redistributions involved will always be considered fair by the agents in the economy.

Second, the analysis clearly identifies that deposit-taking institutions are routinely more systemically risky than other types of financial institutions. However, insurance companies are a readily identifiable group of firms which are consistently highly ranked for systemic risk; and are the most easily identified industry after banking. Thus our analysis supports the argument that insurance companies are a good candidate for systemic oversight, but they are also a less obvious issue than deposit-taking/credit-creating institutions. It is likely that the blurring of functions between traditional insurance products and other financial innovations carried out by insurance companies are contributing to their systemic risk profile. Insurance industry firms which wish to avoid the development of further regulatory oversight would be well-advised to clearly demonstrate their points of difference from credit-creation style activities.

The lessons for investors are also clear. In times of crisis the financial sector firms are critical in whether shocks from one part of the economy are transmitted to others. There are important moral hazard problems in knowing whether the regulators will routinely intervene to dampen the connectivity between sectors during periods of stress. If, on balance, the regulators are expected to intervene in severe cases, then real economy firms will not bear the full brunt of the crisis, making it attractive to have non-financial stocks in a portfolio. The performance of financial sector stocks will depend on the form of intervention undertaken; supporting the financial sector may result in excess returns for capital invested in that sector, but actions such as forced merging and/or resumption of ownership may result in excess loss. The origins of the crisis determine the form of response of the policy makers. Thus while it is good policy to have a number of strategies to implement reduced connectivity between the real economy and the financial sector during periods of extreme stress, it will not be easy for investors to anticipate the form that intervention may take, and hence to profit from it. Without this uncertainty it would be difficult for the policy actions to be effective as these expectations would be priced.

6. Conclusions

In this paper we produce an overall index of systemic risk for the financial sector, and a ranking for each of the firms in the dataset. To this end, we examine the connections between shocks in risks over 500 US companies drawn from the S&P500 index for the period 2003–2011. 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.

Our overall index of systemic risk shows that 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, while these policy interventions were effective in reducing systemic risk as measured by interconnections, they did not alter systemic risk measured by capital shortfall, as shown in Brownlees and Engle (2017).

Our systemic risk ranking suggests the importance of two categories of firms in assessing systemic risk. First, those which consistently rank as the most systemic throughout the sample –including banks such as Wells Fargo, Bank of America and JP Morgan. Second, those firms which may on average rank in the middle of the system, but have the capacity for rapid change, such as AIG and KeyCorp. Financial firms feature prominently in both of these groups. This reinforces 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.[11] The second is to relate the systemic outcomes to 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 pairwise Granger-causality approach in Billio et al. (2012) and Diebold and Yilmaz (2014). Our methodology is flexible enough to accommodate these extensions.

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[11] Dungey et al. (2017) considers evidence for Australia.

A. Data

A.1.

Intraday returns

The raw data consist of 5 min 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.[12] 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. After this process the sample contains 557 stocks. Programs in C+ are available on request to both replicate the data and make alternative selections.

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, 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 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.

A.2.

Realized volatilities

Using the last trade in each 5 min 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_{jt}. More precisely, let r_{jti} be the intraday trade return of firm j on day t at 5-min time $i = 1, \dots, N$. The annualized realized volatility is

$$x_{jt} = 100\sqrt{252}\sqrt{\sum_{i=1}^{N} r_{jti}^2}.$$

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_{jt}; see 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). Thus their inclusion is practically important in attempting to empirically model systemic risk. While the estimator is in principle contaminated by microstructure noise, 5-min data is the commonly used benchmark trade-off between information and noise for liquid assets; see for example 2011 and 2007.

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[12] 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 so we match codes and companies through merger and acquisitions, stock splits and trading halts.

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