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Surfing through the GFC: Systemic risk in Australia

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Abstract

We provide empirical evidence on the degree of systemic risk in Australia before, during and after the Global Financial Crisis. We calculate a daily index of systemic risk from 2004 to 2013 in order to understand how real economy firms influence the outcomes for the rest of the economy. This is done via a mapping of the interconnectedness of the financial and non-financial sectors. The financial sector is in general the home to the most consistently systemically risky firms in the economy. The mining sector becomes occasionally as systemically risky as the financial sector, reflecting the importance of understanding the interrelationships between the financial sector and the real economy in monitoring systemic risks.

Keywords: banking, insurance, systemic risk

JEL classification: G22,G21,G01,G28

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1 Introduction

The Australian financial sector weathered the financial turmoil of international markets during 2007-2013 relatively well, retaining high credit ratings as well as good access to international funding markets, RBA (2009). Although the IMF (2012) asserted that the Australian banking sector is capable of withstanding severe macroeconomic shocks, the Australian Financial System Inquiry (AFSI) Final Report (Treasury, 2014) suggests that an asset value shock of similar magnitude to those experienced in the US or Europe during the Global Financial Crisis would cause Australian banks major distress. It is therefore clear that measuring the level of systemic risk in Australia is crucial.

The AFSI outlines the features of the Australian financial sector, including *i*) the concentrated banking sector, *ii*) the importance of non-interest income, and *iii*) a substantial exposure to housing markets through large on-balance sheet mortgage books.[1] The Australian banking system and the Australian economy have substantial international linkages through financial and trade flows,[2] and the economy is exposed particularly to shocks originating from the volatility of commodity prices and related changes in world demand and supply from its major trading partners, particularly in the recent past with changing demand for mining exports in China.[3] Both trade and financial linkages have been shown to facilitate the transmission of crises and hence systemic risk (see Van Rijckeghem and Weder 2001), while recent evidence also supports the importance of institutional ownership in spreading liquidity shocks across jurisdictions (see Moshirian et al 2014).

This paper examines systemic risk in the Australian financial sector through the interconnectedness of the financial as well as non-financial sector firms. Measuring systemic risk through the networks of financial institutions is a growing empirical literature: for example, Billio et al (2012) and Anufriev and Panchenko (2015) compare snapshots of non-crisis and crisis period networks, while Giraitis et al (2013) and Diebold and Yilmaz (2014), amongst others, estimate time-varying systemic risk via connectivity.

This paper expands upon the existing literature by including both financial and non-

[1]While concentration in the banking sector has been identified by a number of authors as important in understanding the transmission of crises (see Dungey and Gajurel 2014), Engle et al (2014) document cross-country evidence that concentrated banking systems with diversified activities resulting in relatively large non-interest income, such as Australia, are associated with greater banking sector stability.

[2]Banks' foreign net liabilities, denominated largely in foreign currency, are sizeable at around 24 percent of GDP (IMF, 2012), the majority of which is likely to be hedged. However, in times of stress banks may still have difficulty in obtaining a favourable exchange rate at which to replace existing hedges.

[3]See for example Roache (2012), Plumb et al (2013), and Dungey et al (2014c) for recent evidence on the influence of Chinese demand on the Australian economy, particularly with respect to the mining sector.

financial sector firms in our modelling framework. This encompasses the insight that non-financial sectors can be the source of shocks which cause instability in the financial sector. Using a network framework Acemoglu et al (2015) understand the transmission of shocks through banking networks where shocks to the system originate with the real economy investments undertaken by the financial sector. Put differently, the results of jointly modelling the interconnections between financial and non-financial firms support a high degree of interconnectedness, and that the extent of interconnectedness increased during the period of global financial stress from 2008, consistent with the results of Anufriev and Panchenko (2015).

The framework and empirical results of these two papers suggest that there are good reasons to extend the analysis and monitoring of systemic risks to sectors and/or firms which are highly connected within the economy, although outside the financial sector itself. Indeed, our sector level results show that whilst the financial sector is the most consistently systemically risky sector, there have been periods since 2008 when the mining sector has posed equivalent levels of systemic risk. The mining sector includes both some large and consistently risky firms and some non systemic ones, so that at times the combined risk of all mining sector firms can exceed that of the financial sector firms. This result confirms the importance of understanding the interrelationships between the financial sector and the real economy in monitoring systemic risks.[4]

Our firm level results reveal the consistently high systemic risk ranking of the major 4 Australian banks (ANZ, Commonwealth Bank, National Australia Bank and Westpac), but also reveal that the two regional banks in the sample, Bank of Queensland and Bendigo and Adelaide Bank, have seen a significant rise in their systemic risk ranking associated with their growing presence in the national market. Amongst mining sector firms, BHP and Rio Tinto are consistently amongst the most systemic firms, with Rio Tinto consistently in the top 10 after 2010. Other mining sector firms show both great diversity and volatility in their systemic risk rankings. We visualise the results by plotting the sample average systemic risk ranking for each firm against its standard deviation, which clearly reveals both the dominance of financial sector firms amongst the consistently most systemically risky, and the diversity of the mining sector firms, some of which are on average mid-ranked, but with a high standard deviation.

We conclude that the role of the mining sector in the Australian economy, where it is highly interconnected with many other companies in the economy, and particularly with

[4]Anufriev and Panchenko (2015) also carry out a network analysis of industrial sectors in the Australian context, but do not go to firm level in the non-banking sectors.

the financial sector, suggests that monitoring developments in this sector may be important for monitoring systemic risk.

The paper proceeds as follows. Section 2 explains the methodology, while Section 3 describes our dataset, and Section 4 provides the empirical results for the financial and non-financial sectors of the economy, and for selected banks and mining companies. Section 5 concludes.

2 Modelling interconnectedness

2.1 Banks, the real economy, and shocks

The literature on network finance to analyse systemic risk and crises is growing rapidly. Theoretical work shows how the design of the network may lead to systems which are robust during the majority of conditions, but become fragile when exposed to either one large or many small shocks. Early contributions to this literature, such as Allen and Gale (2000), identified the importance of network design and developed many results around robustness, while the issue of fragility emerged later, with Gai and Kapadia (2010) demonstrating vulnerability when connections are more complex. Most recently Acemoglu et al (2015) demonstrate the 'robust but fragile' properties of banking networks using a modelling framework that specifically captures the risk associated with a shock in projects invested in the real economy.

The Acemoglu et al (2015) framework is a 3 period model for multiple risk-neutral banks. At the initial period bank i holds capital k_i which can be invested in loans to real economy firms, where that investment has an uncertain return z_i in period $t = 1$ and a fixed return at $t = 2$. The long term return is not pledgeable. The capital k_i can also be lent to other banks in the economy (interbanking lending) or held as cash reserves.

From the liability side, in period $t = 1$ bank i needs to pay its outside senior obligations (for example pre-contracted expenses such as wages) v_i, and meet all its interbank loan obligations $y_i = \sum_{j \neq i} y_{i\,j}$. The liabilities are therefore $v_i + y_i$. To meet these outgoings at time $t = 1$, the bank has available its hoarded cash, c_i, and the interbank payments it receives from other institutions $\sum_{j \neq i} x_{j\,i}$, or a total of $h_i = c_i + z_i + \sum_{j \neq i} x_{j\,i}$.

The bank meets all its obligations when h_i is at least as much as the liabilities $v_i + y_i$. If a negative shock affects the returns of the loans to the real economy, and the shock is large enough that the bank cannot meet all these obligations, it will first liquidate the loans to the real economy firms, which produces a relatively low return (by model assumption), and then begins the default process paying down creditors in seniority order. This may mean that other banks receive nothing on their interbank liabilities. It is straightforward to see how a negative shock coming from the real economy to a single bank may consequently be propagated across the financial network via the interbank market.

As mentioned, the source of the shock in the Acemoglu et al (2015) model is the stochastic return on the loan to the real economy firm. However, the network diagrams presented in Acemoglu et al (2015) and the many others in the theoretical network finance literature represent only the interlinkages between the banks. Here we take advantage of our modelling framework to specifically take into account the interlinkages between real economy firms and the financial sector.

2.2 An economy-wide network of shocks in risk

To empirically implement our network analysis we analyse both financial and non-financial firms as nodes for the network. A financial 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. In this section we explain the methodology for constructing indexes of systemic risks for the different sectors of the economy, as well as ranking the firms in terms of systemic importance. Practical aspects for the implementation of the methodology are provided in next section.[5]

Each firm is endowed with a level of risk, reflecting the uncertainty associated with the payment of its liabilities. 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.

Let N be the number of firms in the system. 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 coefficient c_{kjt} represents the transmission channel between companies k and j at time t. Its dynamics are given by the strength of the connections, which is

[5] For a more extensive presentation of the methodology used in this paper we refer the reader to Dungey et al. (2013).

captured by the correlations between shocks, denoted by ρ:

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

The system of systemic importances can be written in matrix form as $\mathbf{S}_t = \mathbf{C}_t \cdot \mathbf{S}_t$. The transmission matrix $\mathbf{C}_t$ has zeros in the main diagonal, since a firm does not transmit risk to itself. Every column of $\mathbf{C}_t$ 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.

One of the features of the build-up of a financial crisis is 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 between shocks increases, the network becomes more dense, which translates into an increase of the systemic importances. Let $\mathbf{S}_t^{Fin}$ be the subset of $\mathbf{S}_t$ that contains the N^{Fin} financial institutions. The systemic risk index of the financial sector, denoted GS_t^{Fin}, equals

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

Since $\mathbf{S}_t^{Fin}$ is a subset of $\mathbf{S}_t$, we can choose another subset and easily construct systemic risk indexes for financial sub-sectors, such as materials or energy. Take, for instance, firms that are part of the materials sector (which include the mining companies) and let $\mathbf{S}_t^{Mat}$ be the subset of $\mathbf{S}_t$ that contains these institutions. The materials systemic risk index is the average of $\mathbf{S}_t^{Mat}$:

$$GS_t^{Mat} = \frac{1}{N^{Mat}} \sum_{k=1}^{N^{Mat}} S_{kt}^{Mat}.$$

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

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

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 while incorporating firm characteristics. Indeed, this apparent simplicity belies its demonstrated effectiveness. The approach is that used by Google to drive its search engines when guiding the internet user through the complexity of interconnections on the web, as originally proposed in Brin and Page (1998).

3 Data

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.

The expectations are computed with ARFIMA models. These models are convenient filters for realized volatilities since they capture the main stylized facts, namely short- and long-memory (Luciani and Veredas, 2015). The realized volatilities are estimated simply by summing the squared intraday returns over the day. There are two reasons for this choice. The first is the now well-known higher performance of realized volatility in estimating and forecasting volatility in financial markets; see Andersen et al. (2003, 2007). The second is that realized volatility retains abrupt disruptions, or jumps, in price series, and these have been shown to be both an important component of information transmission and useful in detecting crisis conditions; see Patton and Verardo (2012), Aït-Sahalia et al. (2014), Dungey et al. (2014b).

The intraday dataset consists of 5 minute observations on 300 ASX listed firms drawn from the population of all firms listed on the ASX during the period 2004-2013, using the Australian Tick History dataset from SIRCA. There are significantly more entry and exit of firms listed on the ASX than on the larger S&P500 index used in the US analysis of Dungey et al. (2013,2014a), requiring some adaptions to deal with this mobility and with firms with low presence in the index. Firms with more than 200 missing observations in the sample period were excluded, reducing the number of firms to 168. The remaining database retains a substantial portion of data sub-periods with missing data for individual stocks. The least data are available at the beginning and end points of our sample series. Despite adapting our estimations to cope with the changing sub-sample sizes at the end of the sample particularly displays some results which appear to be related to the exit of a number of firms around the first quarter of 2011. We discuss the impact of these data problems where they affect the results. The data are cleaned for splits and mergers and we have tracked and accounted for changes in RIC code.

The classification of the firms by sectors is in Table 1. While some sectors consist of very few firms (such as semi-conductors and retailing), others consist of more than 10 (such as capital goods, energy, materials and real state). The latter sectors will be the focus on our analysis, along with individual analysis for banks and mining firms.

4 Empirical Results

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. Every time the window is rolled, the shocks and the correlations between them are computed. We begin this section with the analysis of the financial sector, followed by the analysis of the remaining prominent sectors. The second part of the section focuses on individual companies, namely banks and mining firms.

4.1 The financial sector

The GS index for the financial sector – banks, diversified financials, and insurers – is given in Figure 1, where the vertical lines indicate the sub-periods at the beginning of the sample (where data availability is less complete) and the end of the sample (where the exit of a number of firms from the data sample creates some analytical challenges).

While there is no consistent or prolonged build-up of systemic risk in the Australian financial sector in our sample there is a pronounced increase in the index from June 2006 to January 2007. This appears to end around the period at which the Shanghai wobble of early 2007 is resolved. Although the financial index displays some intermediate building of pressure around the time of the Northern Rock problems and the support offered by the ECB in August 2007, this is again resolved by early 2008 and the build up in systemic risk to October 2008 is relatively small in comparison with earlier episodes. After that point, despite the difficult international conditions, the systemic risk of the financial sector declines, although it is interrupted in this trend by a spike associated with the Greek debt crisis. From 2011 onwards, the systemic risk index for the financial sector increases, reaching a peak at the end of the sample. However, this rising trend from June 2012 is during the period where our data sample is confronted by a relatively large number of missing data points.

Next, we provide two comparisons. The first is with the SRISK index of the Stern NYU V-lab project (Acharya et al., 2010, and Brownlees and Engle, 2011). SRISK and our index are complementary. While ours gives information about the interconnected nature of the economy, SRISK gives information about the capacity of the economy to absorb a financially traumatic shock. When both measures 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. The SRISK measure for the Australian financial sector

– provided in Figure 2 – is relatively volatile, increasing from negligible in 2007 to over US$100 billion by 2009, and after recovery climbing again to US$120 billion in 2012.

The second comparison is with our GS index calculated for the US market. While the systemic levels of the Australian financial sector do not seem to follow the international developments, the GS index for the US represents them clearly. Figure 3 – taken from Dungey et al. (2013) – reproduces the GS index calculated for the US. The systemic risk pressure was building well prior to the problems of 2007-2008. The dramatic drop in interconnectedness risk in the US in October 2008 is strongly associated with the rescue of AIG, Fannie Mae, and Freddie Mac, and more generally the Troubled Assets Relief Program (TARP), which disconnected the financial sector from real economy firms – investors reflected that although the financial sector chaos was destined to result in poor economic outcomes, there would now be protection from potential augmentation of the cycle through further reductions in bank credit as the economy contracted. This downward trend brought systemic risk in the economy back to the levels of mid-2007, before a further increase which is aligned with the building tensions in the sovereign debt crisis of Greece (which was offered some respite with the final agreement of an IMF support plan in April 2010).

4.2 Sectors from the real economy

A number of sectors in our sample are represented by a relatively small numbers of stocks, as shown in Table 1, so that analysis of them really represents analysis of individual companies. Consequently we concentrate on those sectors with 10 or more component stocks: capital goods, energy, materials, and real estate.

Figure 4 provides the GS_t indices. For comparison purposes, the grey line is the GS_t index for the financial sector. The systemic risk index for the financial sector is generally higher than for other sectors, reflecting the established view that the financial sector is one of the most vulnerable areas of any economy and justifying regulatory oversight of this sector. The capital goods sector, which typically contains long-term capital investment projects, is one of the least systemically risky in the sample (including those not shown here) and typically there are very few instances where it is not the lowest value index for all sectors. The real estate sector represents companies with strong involvement in the commercial property market, and as such it reflects changing conditions in both the retail environment and general property market conditions.

The indices for materials and energy are more interesting. They increased fairly consistently for both across the majority of the sample. The energy index rose considerably over the period until mid-2010, and then remained relatively stable for an extended period. The drop in the index at the end of the period is strongly associated with one of the data problems evident in the end part of our sample, reflecting the re-entry of DrillSearch Energy into the database after an absence of several years. The other constituent stocks at this time show a mixed profile of rising and flat indices for systemic risk. Overall, the systemic risk index of the energy sector reflects the reductions in energy demand during the economic slowdown and recovery after the GFC.

The materials sector contains primarily mining related companies. The mining companies have experienced particularly strong growth since the 1990s, albeit with some slowdown towards the end of the sample due to declining Chinese demand and reduced confidence in commodity exports associated with the GFC in 2008; see Roache (2012). The importance of the mining sector, and Chinese demand in particular, is documented in Plumb et al. (2013), Dungey et al (2014c). In 2012, the mining sector outstripped the contribution of manufacturing to Australian output, at just over 7% of GDP, rising further to 8% in 2014.[6] Despite the slowdown, the systemic risk index for the materials sector rises steadily over the sample, and reaches nearly the same level as the financial sector index in March 2009; however, it exceeds the financial sector index during the first six months of 2011.

That the materials sector becomes as systemically risky as the financial sector during this period reflects the potential importance of understanding the interrelationships between the financial sector and the real economy in monitoring systemic risks in the economy. Indeed, if the financial sector is facing systemic risk due to its exposure to a dominant sector of the economy this poses quite different policy issues to exposing the real economy to risks emanating from the behaviour of the financial sector itself. A recession which begins with a real economy shock, say a reduction in demand due to changes in preferences away from Australian exports, will reduce loan performance in the financial sector and potentially result in tighter credit reinforcing the contractionary pressures in the real economy. These shocks can be tackled via standard monetary policy easing to improve credit conditions. In contrast, a shock which results from the financial sector itself immediately imposes credit restrictions on a well-performing real economy sector, resulting in potential moral hazard associated with easing monetary policy to aid the real economy via the financial sector. Finding the cause of shocks is clearly important in formulating

[6]Source: Australian Bureau of Statistics catalogue 5206 Table 37 GVA figures.

appropriate policy response.

4.3 Individual companies

We have shown so far the indices of systemic risk for each sector. The monitoring of specific firms is also of interest. In this section we focus on the individual rankings of banks and of mining companies, as they are among the most important sectors of the Australian economy.

4.3.1 Banks

The four major national Australian banks (ANZ, Commonwealth Bank (CBA), National Australian Bank (NAB), and Westpac (WBC)) and two regional banks (Bendigo and Adelaide, Bank of Queensland) are contained in our dataset. Based on their systemic importances, we compute their ranking among all firms in our sample. Figure 5 shows the rankings for each of the 6 banks.

First, note that the regional banks are on a different scale than the four majors. The regional banks are the smallest of those in our dataset, with deposits of around the 10-15% level of the larger banks. However, they have had an increasing presence in the Australian market. The Bendigo and Adelaide bank in its current form is the result of a merger between two regional institutions – the Bendigo Bank and the Adelaide Bank – in November 2007, and its consequent growing importance is evident in its move from being ranked at between 80-100 in our systemic ranking of all the firms near the beginning of the sample, to consistently in the top 30 most systemically risky firms since August 2011. The Bank of Queensland has a slightly larger deposit base than the Bendigo and Adelaide bank, but has also seen a fall in its systemic risk ranking from between 80-100 for much of the pre-2008 period during a period when it was undertaking significant expansion to its operations across mainland states and territories, and mergers with West Australian and other Queensland building societies. It experienced a rapid move towards a higher ranking with the worsening international credit conditions in 2008, and was ranked as low as the top 20 during the period 2010-2011 during which it was heavily exposed to losses from the extensive damage due to the Queensland floods. It has subsequently dropped back in the rankings by the end of the period.

The four major banks are all consistently in the top 30 of the most systemically important firms in the Australian data sample. ANZ has the smallest deposit base of these four banks,[7] but is consistently the most systemically risky of the banks in the pre-2008 sample. Since then it has only moved beyond the top 15 of the firms for a short period in September-November 2011. However, this drop in the ranking for the period from 2009 to 2011 is evident for all the major banks, particularly CBA, WBC and somewhat NAB. It reflects less of a reduction in systemic risk in the banks, although international conditions had eased, and more of an increase in the systemic risk associated with mining and energy firms, particularly BHP, Rio Tinto and Arrium and Woodside, as discussed below. There is slightly retrospective evidence of increase in systemic risk ranking for NAB and WBC in the lead-up to the 2007-08 period, and during 2008 the banks were clearly a point of stress for systemic risk. However, the merger between WBC and St George Bank which occurred during the height of the international stress in December 2008, did not have a long-lived effect on the systemic ranking of WBC. In the more recent period the systemic risk rankings for CBA and NAB have placed them amongst the top 5 most systemic firms in the sample.

Another large institution in Australia is Macquarie Financial which is contained amongst the diversified financials group and includes Macquarie Bank. The dataset for this group is limited to the second half of the sample from June 2009, making it difficult to perform an overall analysis of the firm. However, it is worth noting that Macquarie Financial is rarely outside the top 10 most systemically risky firms in the sample, ranking outside the top 10 only briefly in 2009 and 2011.[8] Like the CBA and the NAB the most recent period places them consistently amongst the top 5 most systemic firms in the sample, and regularly ranked as either first or second in the systemic risk rankings. This large financial services conglomerate is clearly very integrated with the Australian financial and real economy sectors. Macquarie Bank qualifies as an Australian ADI, and as such is monitored as a bank by the Australian Prudential Regulatory Authority (APRA).

4.3.2 Mining and energy firms

The diversity of systemic risk rankings in the materials sector is pronounced, usually containing at least one firm in the top 10 most systemically risky and one in the 10 least systemically risky. Thus there is no typical firm for this sector.

However, it is informative to consider several firms which do enter the top 10 most sys-

[7]Source: Australian Prudential Regulatory Authority Monthly Banking Statistics, downloaded December 10, 2014

[8]More precisely, out of the 911 days that it is part of the sample, Macquarie Financial ranks first 74 days, second 314, and third 94.

temically risky firms during the sample period: Arrium, Alumina, BHP, Boral, Newcrest Mining and Rio Tinto. Figure 6 presents their rankings. While Boral has remained relatively stable over the sector in its systemic rank, Alumina has become steadily less highly ranked and Newcrest Mining has moved from the most systemically risky in the 2006-2007 period to the other end of the ranking by the end of the sample. Arrium shows a high degree of systemic risk in 2009-2011. BHP and Rio Tinto are consistently in the top 50 most systemic firms, but show somewhat different patterns with BHP going through a less systemically risky period in 2011 whilst Rio Tinto has been consistently in the top 10 most systemically risky firms from 2010.

4.4 Identifying Consistently Risky Firms

By plotting the average firm ranking against its standard deviation we obtain a visual representation of the systemic risk measures over time by the different sectors shown in Figure 7. We denote this graph the 'boomerang curve' due to its obvious resemblance to that iconic shape.

Observations in the bottom left corner of the figure represent firms which are consistently systemically risky, that is they have a low average ranking in the systemic rank and they do not deviate much from that observation. Firms at the other end of the horizontal axis, with a high average systemic rank and low standard deviation are those which are consistently not systemically risky in the sample. The other category of interest is those firms near the apex of the boomerang, these are firms which have a mid-ranking systemic risk, but have shown a substantial variation around that, supporting evidence that they can become systemically risky – a number of the materials firms examined in detail in the previous subsections show evidence of this possibility.

Figure 7 also differentiates two specific sectors of interest from other firms in the economy. The first of these is financial sector firms. The filled black circles represent banks, the black Xs represent insurance, while the grey Xs represent diversified financials. The clear clustering at the bottom left axis of the figure represents the major banks in our analysis - noting that grey X in the lower left hand corner of the figure represents Macquarie Financial which includes Macquarie Bank - followed by the insurance companies. This is a feature also noted for the US in Dungey et al. (2014a) which they cite as empirical support for prudential regulatory oversight of the insurance sector, an issue which is hotly debated in the international context but less so in Australia given the existing oversight of the insurance industry by APRA; see Biggs and Richardson (2014) for an overview of the issues.

The open squares represent firms in the materials sector, and these clearly span the full range of possibilities; from two firms consistently in the top 20 (Rio Tinto and BHP) to those ranked near the very right hand end of the horizontal axis. A cluster also exists with an average rank near the middle of the group, but with generally relatively high variance.

The insights from the boomerang curve confirm that the financial sector is in general the home to the most consistently systemically risky firms in the economy. These firms are highly interconnected. Also, the importance of the materials sector, which includes the large mining sector, is apparent. A number of these firms are consistently risky. The existence of a relatively important sector in the economy, with which the fortunes of many other firms in the economy including the financial sector are intertwined, creates a further sector with identifiable risks to the economy. This is by no means a call to regulate these firms in the same manner as the financial sector, but rather a first attempt to understand how real economy firms may influence the outcomes for the rest of the economy via a mapping of the interconnectedness of the financial and non-financial sector.

5 Conclusion

We find that the financial sector displays the most systemic risk, and contains the most consistently systemically risky firms. This is in line with the existing focus on the financial sector in policy and academic discourse on regulatory policy. However, we also document that the systemic risk for Australia's significant mining sector can at times exceed that from the financial sector, and that a small number of large mining sector companies, specifically Rio Tinto and BHP, are also consistently systemically risky.

The evidence is consistent with the Acemoglu et al. (2015) proposed framework that shocks originating in the non-financial sector may be an important source of systemic risk for an economy. This interconnectedness between financial and non-financial sectors of the economy poses an extra dimension to understanding the origins and evolution of systemic risk.

References

Acemoglu, D., A. Ozdaglar, and A. Tahbaz-Salehi (2015). Systemic Risk and Stability in Financial Networks. American Economic Review 105(2), 564-608.

Acharya, V., L. Pedersen, T. Philippon, and M. Richardson (2010). Measuring systemic risk. Technical report, New York University.

Aït-Sahalia, Y., J. Cacho-Diaz, and R. J. A. Laeven (2014). Modeling financial contagion using mutually exciting jump processes. Forthcoming Journal of Financial Economics.

Allen, F., and D. Gale (2000). Financial contagion. The Journal of Political Economy 108, 1, 1-33.

Andersen, T., T. Bollerslev, and F. X. Diebold (2007). Roughing it up: including jump components in measuring, modeling and forecasting asset return volatility. Review of Economics and Statistics 89, 4, 701-720.

Andersen, T., T. Bollerslev, F. X. Diebold, and P. Labys (2003). Modeling and forecasting realized volatility. Econometrica 71, 2, 579-625.

Anufriev, M. and V. Panchenko (2015). Connecting the dots: econometric methods for covering networks with an application to the Australian Financial Institutions. Research Working Paper Series, CIFR. Working Paper No.054/2015 / Project No. E233.

Biggs, J., and Richardson, M. (2014) (eds) Modernizing Insurance Regulation, Wiley, New Jersey.

Billio, M., M. Getmansky, A. Lo, and L. Pelizzon (2012). Econometric measures for connectedness and systemic risk in the finance and insurance sectors. Journal of Financial Economics 104, 535-559.

Brin, S., and Page, L. (1998). The anatomy of a large-scale hypertextual Web search engine. Computer Networs and ISDN Systems, 30, 107-117.

Brownlees, C. and R. Engle (2011). Volatility, correlation and tails for systemic risk measurement. Technical report, NYU. manuscript.

Diebold, F. and Yilmaz, Y. (2014). On the network typology of variance decompositions: measuring the connectedness of financial firms. Journal of Econometrics 182(1), 119-134.

Donald, S., B. Arnold, H. Bateman, R. Buckley, and K. Liu (2013). The implications of complexity for systemic risk in the superannuation system. Research report, CIFR. CLMR Research Paper Series. Working Paper No.13-3.

Dungey, M., R. A. Fry-McKibbin, and V. Linehan (2014c). Chinese Resource Demand and the Natural Resource Supplier. Applied Economics 46, 167-178.

Dungey, M. and D. Gajurel (2014). Contagion and banking crisis - international evidence for 2007 - 2009. Manuscript.

Dungey, M., M. Luciani, and D. Veredas (2014a). Emergence of Systemically Important Insurers. Research report, CIFR. Working Paper No.WP038/2014 / Project No.E102.

Dungey, M., M. Luciani, and D. Veredas (2013). Googling SIFIs. Technical report, University of Tasmania. Working paper.

Dungey, M., M. Matei, and S. Treepongkaruna (2014b). Identifying Periods of Financial Stress in Asian Currencies: The Role of High Frequency Financial Market Data. Technical report, University of Tasmania. Working paper.

Engle, R., F. Moshirian, S. Sahgal, and B. Zhang (2014). Banks non-interest income and global financial stability. Research report, CIFR. Working Paper No.015 / 2014.

Gai, P. and S. Kapadia (2010). Contagion in financial networks. Technical report, Bank of England. Working paper 383.

Giraitis, L., G. Kapetanios, A. Wetherilt, and F. Zikes (2013). Estimating the dynamics and persistence of financial networks, with an application to the sterling money market. Forthcoming Journal of Applied Econometrics.

IMF Country Report (2012) No. 12/308.

Kiyotaki, N. and J. Moore (2002). Balance-sheet contagion. The American Economic Review 92, 46-50.

Luciani, M. and D. Veredas (2015). Estimating and Forecasting Large Panels of Volatilities with Approximate Dynamic Factor Models. Journal of Forecasting 34(3) 163-173.

Lutzenkirchen K., D. Rosch, and H. Scheule (2014) Ratings based capital adequacy for securitizations. Research report, CIFR. Working Paper No.010/2014 / Project No. E001.

Moshirian, F., A. Subrahmanyan, C. Wee, and B. Zhang (2014). Research report, CIFR. Working Paper.

Patton, A. J., and M. Verardo (2012). Does Beta move with news? Firm-specific information flows and learning about profitability. Review of Financial Studies 25(9), 2789-2839.

Plumb, M., C.Kent, and J. Bishop (2013). Implications for the Australian economy of strong growth in Asia. Research Discussion Paper 2013-03, Reserve Bank of Australia.

Roache, S. (2012). China's impact on world commodity markets, IMF Working Paper 12/115.

RBA (2009). Financial Stability Report. March.

Treasury (2014). Financial System Inquiry Final Report. The Australian Government the Treasury. November.

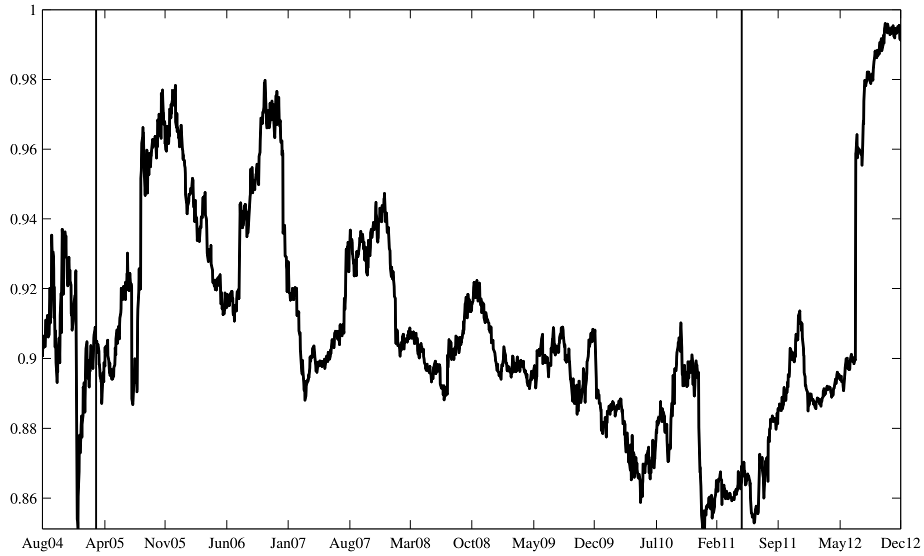
Van Rijckeghem, C. and B. Weder (2001). Sources of contagion: is it finance or trade? Journal of International Economics 54(2), 293-308.

Figures and Tables

Table 1: CLASSIFICATION OF STOCKS BY INDUSTRY

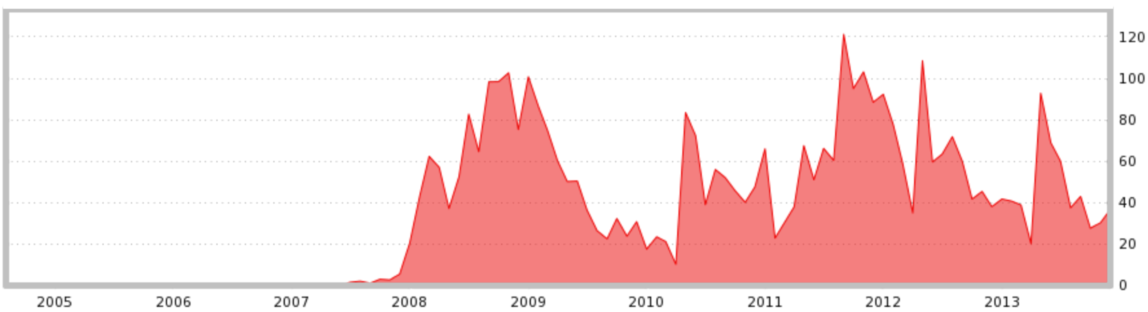
Sector	**Number of stocks**
Banking	6
Capital Goods	11
Commercial and Professional Services	8
Consumer Durables and Apparel	3
Consumer Services	5
Diversified Financials	6
Energy	15
Food and Staples Retailing	2
Food, Beverage and Tobacco	5
Health Care Equipment and Services	7
Insurance	5
Materials	32
Media	7
Pharmaceuticals	3
Real Estate	10
Retailing	3
Semi-conductors and Semiconductor Equipment	1
Software and Services	7
Telecommunication Services	5
Transportation	6
Utilities	3
Other	18

Figure 1: Systemic Risk Index for the Australian Economy



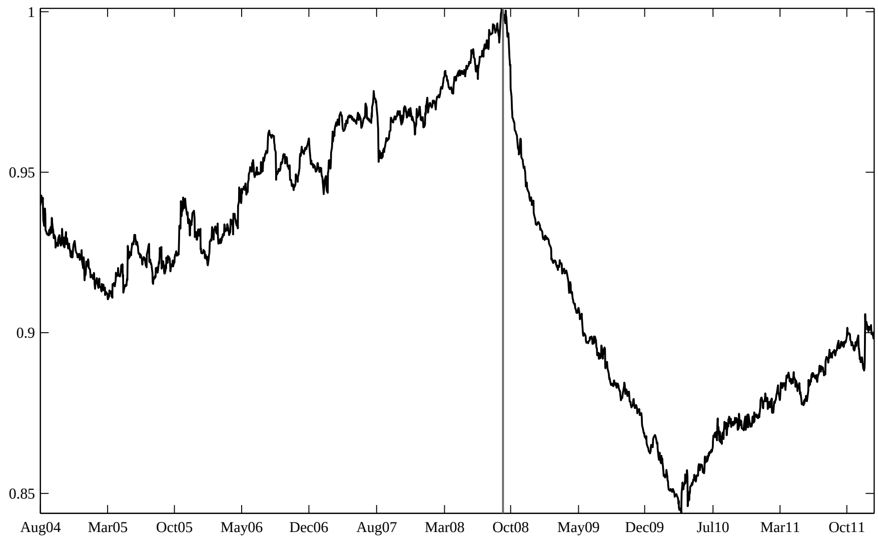
The thick black line is the GS_t index for the Australian economy as defined in (3). The two vertical thin black lines indicate the sub-periods at the beginning of the sample where data availability is less complete and the end of the sample where the exit of a number of firms from the data sample creates some analytical challenges.

Figure 2: SRISK for Australian Financials



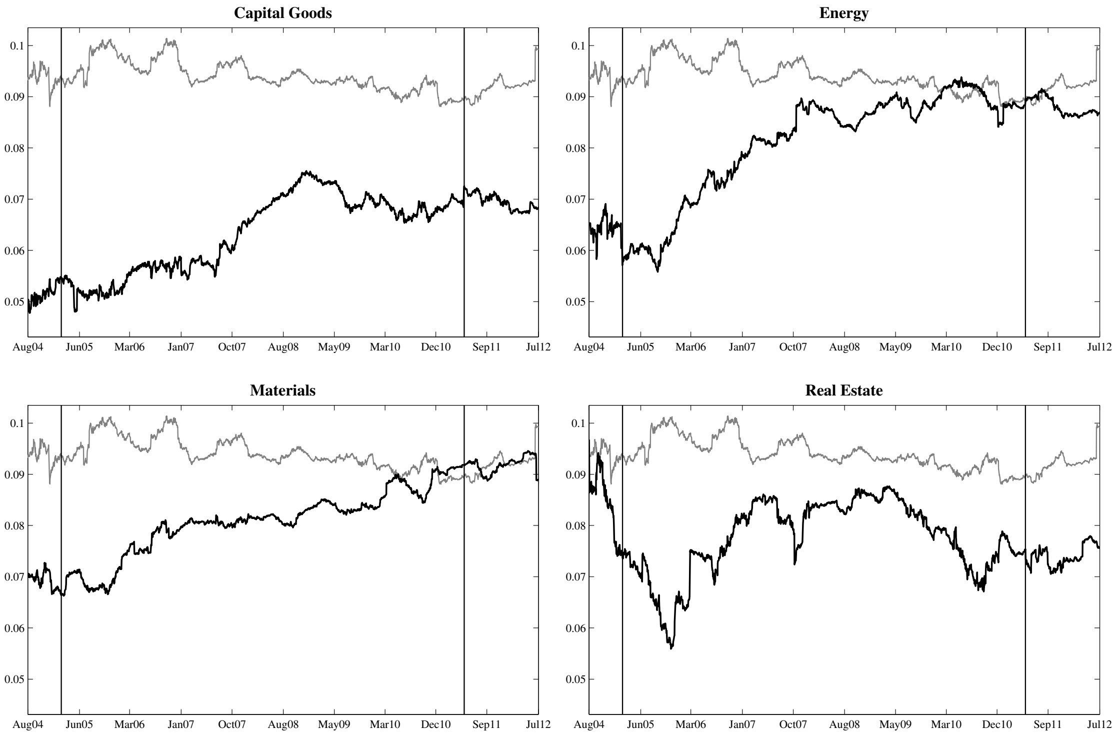
This plot shows the SRISK index for the Australian economy. This plot was downloaded from the V-lab website (`http://vlab.stern.nyu.edu/welcome/risk/`) on March 19, 2015.

Figure 3: US GS–INDEX



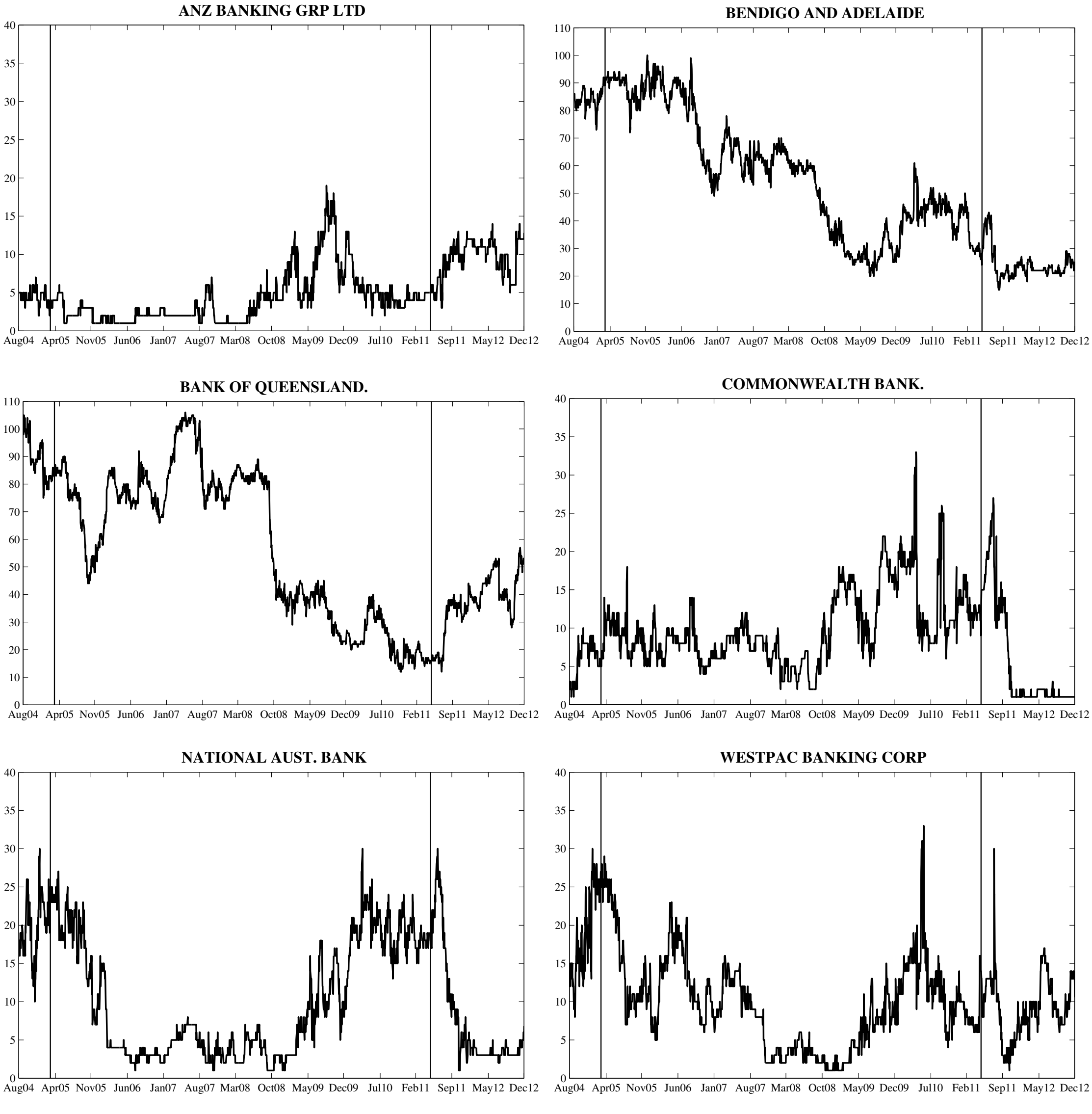
Source: Dungey et al. (2013).

Figure 4: SYSTEMIC RISK FOR SELECTED SECTORS



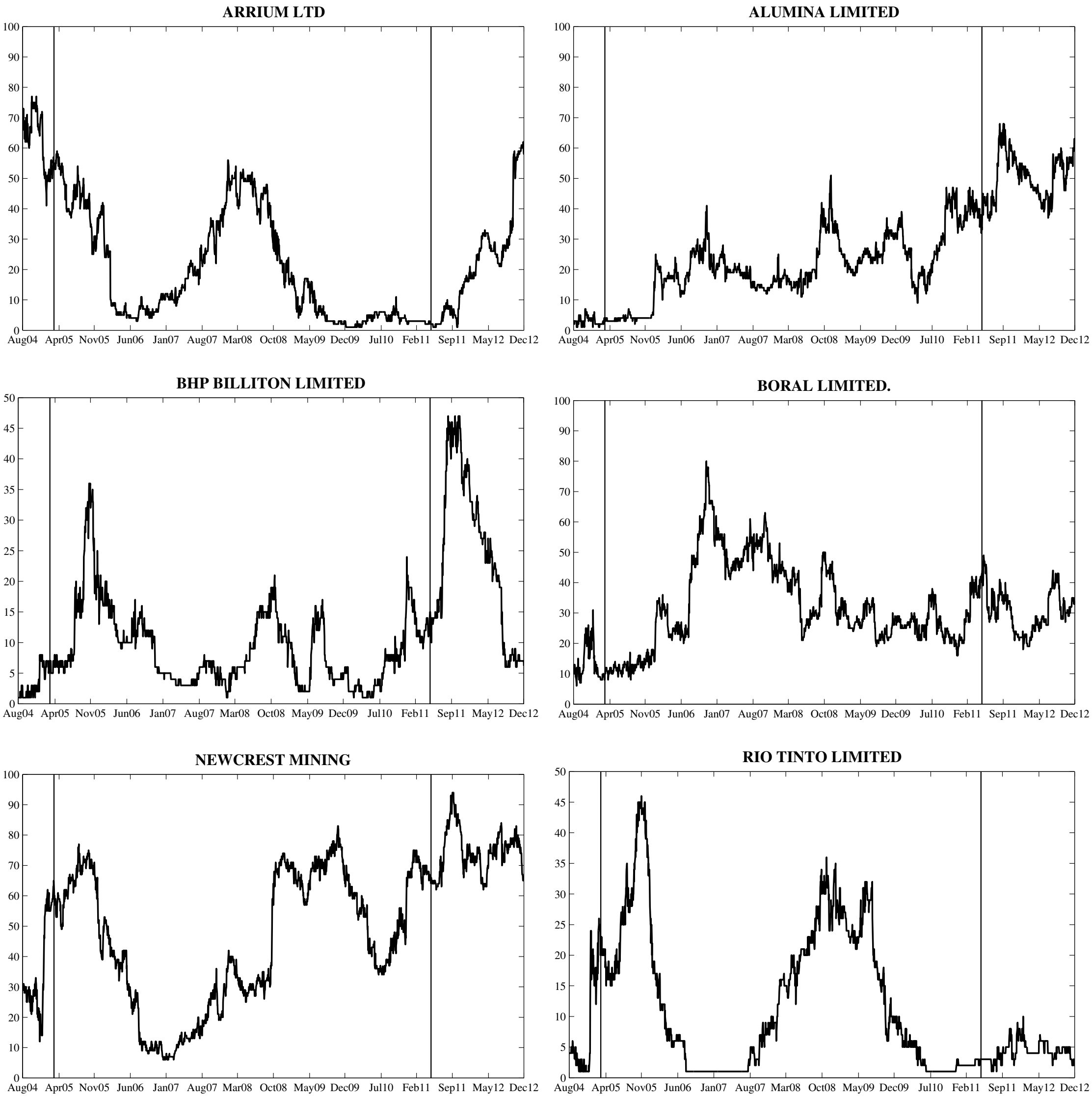
In each plot the thick black line is the sectorial GS_t index and, for comparison purposes, the grey line is the GS_t index for the financial sector. The two vertical lines indicate the sub-periods at the beginning of the sample where data availability is less complete, and the end of the sample where the exit of a number of firms from the data sample creates some analytical challenges.

Figure 5: Systemic Risk Ranking for Individual Australian Banks



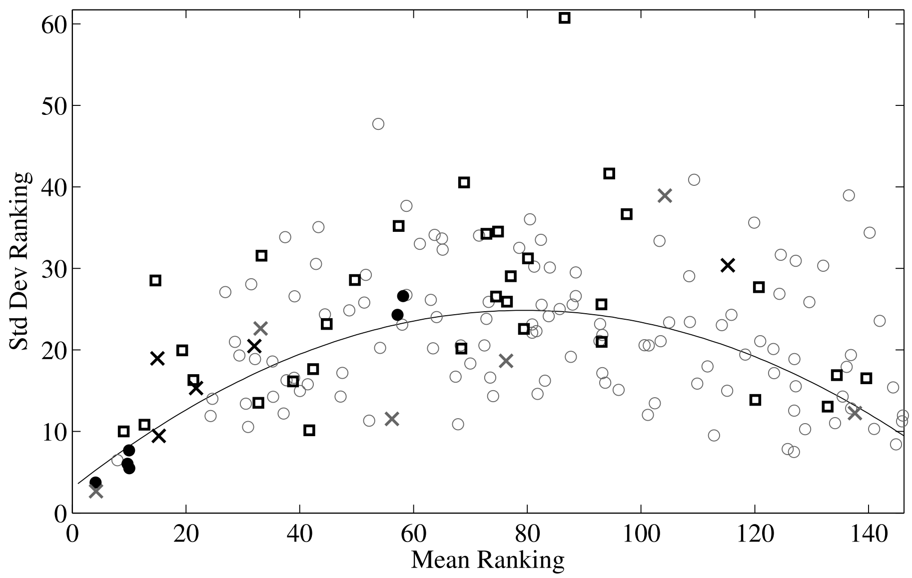
In all plots the thick black line is the systemic ranking of the corresponding bank. The two vertical thin black lines indicate the sub-periods at the beginning of the sample where data availability is less complete, and the end of the sample where the exit of a number of firms from the data sample creates some analytical challenges.

Figure 6: Systemic Risk Ranking for Individual Mining Sector Companies



In all plots the thick black line is the systemic ranking of the corresponding mining firm. The two vertical thin black lines indicate the sub-periods at the beginning of the sample where data availability is less complete, and the end of the sample where the exit of a number of firms from the data sample creates some analytical challenges.

Figure 7: The Boomerang Curve



The black squares represent companies in the materials sector, the filled black circles represent banks, the black Xs represent insurance, while the grey Xs represent diversified financials. Open circles represent the remaining firms.

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