Identifying systemically important companies in the entire liability network of a small open economy

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Abstract

To a large extent, the systemic importance of financial institutions is related to the topology of financial liability networks. In this work we reconstruct and analyze the – to our knowledge – largest financial network that has been studied up to now. This financial liability network consists of 51,980 firms and 796 banks. It represents 80.2\% of total liabilities towards banks by firms and all interbank liabilities from the entire Austrian banking system. We find that firms contribute to systemic risk in similar ways as banks do. In particular, we identify several medium-sized banks and firms with total assets below 1 bln. EUR that are systemically important in the entire financial network. We show that the notion of systemically important financial institutions (SIFIs) or global and domestic systemically important banks (G-SIBs or D-SIBs) can be straightforwardly extended to firms. We find that firms introduce slightly more systemic risk than banks. In Austria in 2008, the total systemic risk of the interbank network amounts to only 29\% of the total systemic risk of the entire financial network, consisting of firms and banks.

Keywords: credit network, systemic importance, bank-firm relationships, interbank network, systemic risk, financial regulation, contagion

JEL: D85, G01, G18, G21

1. Introduction

The financial crisis of 2007–2008 was sparked by the collapse of a relatively small – now famous – investment bank and propagated through the financial system, bringing the world financial system to the brink of collapse. Through interrelationships between the financial and the real economy, the financial crisis spread quickly and was followed by a global economic downturn, the Great Recession. Potentially, also the opposite could happen: a financial crisis could originate in the real economy and spread to the financial system, making the study of interrelationships between the financial and the real economy more important than ever.

In response to the financial crisis, the Basel III framework recognizes systemically important financial institutions (SIFIs) and, in particular, global and domestic systemically important banks (G-SIBs or D-SIBs) and recommends increased capital requirements for them – the so called “SIFI surcharges” (Bank for International Settlements, 2010). In this context several network-based measures that identify systemically important financial institutions have been proposed and applied recently (Battiston et al., 2012; Markose et al., 2012; Billio et al., 2012; Thurner and Poledna, 2013; Poledna and Thurner, 2016; Leduc et al., 2017; Poledna et al., 2017). These approaches bear the notion of the systemic importance of a financial institution within a financial network and rely on network centrality or on closely related measures.

These network-based approaches typically work well in small financial networks like banking networks with a relatively small number of financial institutions, usually less than a thousand. A serious disadvantage of centrality measures is, however, that the corresponding value for a particular institution has no clear interpretation as a measure for expected losses. A solution that solves this problem is the so-called “DebtRank”, a recursive method, suggested by Battiston et al. (2012), which quantifies the systemic importance of financial institutions in terms of losses that they would contribute to the total loss in case of a default. Since data on financial networks is hard to obtain outside central banks and is typically only available for small banking networks, there have also been several attempts to quantify systemic importance of institutions without the explicit knowledge of the underlying networks (Adrian and Brunnermeier, 2011; Acharya et al., 2012; Brownlees and Engle, 2012; Huang et al., 2012).
These developments have spurred research on financial networks. Driven by data availability, research on financial networks has mainly focused on default contagion: mostly, on direct lending networks between financial institutions (Upper and Worms, 2002; Boss et al., 2004, 2005; Soramäki et al., 2007; Iori et al., 2008; Căjueiro et al., 2009; Bech and Atalay, 2010; Fricke and Lux, 2014; Iori et al., 2015), but also on the network of derivative exposures (Markose et al., 2012; Markose, 2012). Research on financial multi-layer networks that considers multiple channels of contagion, has only appeared recently. Poledna et al. (2015) and León et al. (2014) study the interactions of financial institutions on different financial markets in Mexico and Colombia, respectively.

To our knowledge, there exist only a few works that empirically study the interrelationship between the financial and the real economy. These studies focus on Japan and are mainly concerned with the topology of credit networks between banks and large firms (Fujiwara et al., 2009; De Masi and Gallegati, 2012; Aoyama, 2014; Marotta et al., 2015). Additionally, De Masi et al. (2011) and Miranda and Tabak (2013) study credit networks in Italy and Brazil, and Lux (2016) develops a theoretical model of a bipartite credit network between banks and the non-bank corporate sector. De Masi et al. (2011) and De Masi and Gallegati (2012) use network analysis to study the credit networks in Italy and Japan and Fujiwara et al. (2009) and Marotta et al. (2015) investigate the evolution of the network structure in Japan. Marotta et al. (2015) further perform community detection, identifying communities composed of both banks and firms.

Miranda and Tabak (2013) and Aoyama (2014) make the first attempt to empirically study systemic risk in credit networks in Japan and Brazil. Aoyama (2014) uses DebtRank to study risk propagation from banks to firms with a dataset provided by Nikkei Inc. that contains approximately 2,000 firms and 200 banks in Japan, but does not include interbank data. Miranda and Tabak (2013) perform the first study that includes interbank and firm loans. However, the used dataset is relatively small and contains only about 50 banks and 351 firms in Brazil.

In this work we extend the existing literature by reconstructing and analyzing a large financial network that not only includes all interbank liabilities but also nearly all liabilities and deposits between banks and firms. We do this by combing datasets that contain annual financial statements of nearly all firms and banks in Austria (approximately 170,000 firms and close to 1,000 banks) with anonymized interbank liabilities from the Austrian banking system. The reconstruction of this large financial network of firms and banks allows us to identify systemically important firms by employing DebtRank to financial networks as in Thurner and Poledna (2013). We estimate the share of systemic risk introduced by firms and we compare the systemic risk of the interbank network with the systemic risk of the entire financial network consisting of firms and banks. We show that the notion of systemically important financial institutions (SIFIs) or global and domestic systemically important banks (G-SIBs or D-SIBs) can be straightforwardly extended to firms.

The paper is structured as follows. Section 2 provides an overview of the datasets used in this study. In section 3 we explain the methodology to reconstruct the entire financial network. In sections 4 and 5 we present the results by first presenting classical network statistics of the entire financial network, followed by an analysis of systemic importance of firms and banks. Finally, section 6 discusses the results and provides conclusions.

2. Data

The data used for this analysis consists of two main parts, annual financial statements of nearly all firms and banks in Austria and anonymized interbank liabilities from the Austrian banking system. Financial statements of firms are taken from the SABINA database1, which provides information on about 170,000 firms in Austria. This database contains company financials in a detailed format with up to 10 years of history, and additionally, data on shareholders and subsidiaries, activity codes and trade descriptions, and stock data for listed companies. The database includes bank-firm relationships and allows us to identify which firm is a customer of which bank.

Financial statements of banks are made publicly available by the Austrian Central Bank (OeNB)2. Interbank data provided by the OeNB contains fully anonymized and linearly transformed interbank liabilities from the entire Austrian banking system over 12 consecutive quarters from 2006-2008. The dataset additionally includes total assets, total liabilities, assets due from banks, liabilities due to banks, and liquid assets (without interbank assets/liabilities) for all banks, again in anonymized form.

There are 106,919 firms and 796 banks that provided a financial statement in the calendar year 2008. Figure 1 shows a stacked bar chart of the different liabilities found in the balance sheets filed in the calendar year 2008, aggregated by the number of banks associated with each firm. In fig. 2 the number of banks associated with each firm is shown. Approximately 48.6% of the firms representing about 80.2% of total liabilities towards banks can be associated with one or more banks. Firms that can not be associated with a bank are excluded from the analysis. Since it is not compulsory for small firms to provide an exact breakdown of different liabilities, we estimate liabilities towards banks with the average ratio of firms in the same line of business, as indicated by their OeNACE code Wirtschaftskammer Österreich (2008). We now reconstruct the liability network of 796 banks and 51,980 firms representing 80.2% of total liabilities towards banks by firms and all interbank liabilities.

1The SABINA database is provided by Bureau van Dijk, see https://www.bvdinfo.com/en-us/our-products/company-information/national-products/sabina.
2https://www.oenb.at/jahresabschlusski/jahresabschlusski
3. Reconstruction of the liability network

We combined datasets from different sources to create a network that represents the liabilities and assets of the Austrian economy. The resulting bipartite network \( G = (F, E) \) consists of two disjoint sets of nodes: banks \( B \) and firms \( C \), for which the following equations hold,

\[
B \cup C = F \quad \quad B \cap C = \emptyset \quad \quad |B| = b \quad \quad |C| = c .
\]

The links either connect banks with other banks (interbank liabilities), banks with firms (deposits of firms at banks), or firms with banks (liabilities of firms). The weighted adjacency matrix

\[
L_{n \times n} = \begin{pmatrix} B_{B} & B_{BC} \\ B_{CB} & C \end{pmatrix} , \quad n = c + b , \quad (1)
\]

is called the liability matrix, where each entry \( L_{ij} \) indicates the liability that node \( i \) (which is a bank if \( i \leq b \) and a firm if \( i > b \)) has to node \( j \) (the same applies here). It is partitioned into the following four parts:

1. interbank network \( B_B \), connecting banks with banks,
2. bank-firm network \( B_C \), containing information about deposits firms have at financial institutions,
3. firm-bank network \( C_B \), containing information about liabilities firms have to financial institutions,
4. firm-firm network \( C_C \) with inter-firm liabilities, omitted in this work thus \( CC_{xy} = 0 \) for all \( x, y \in [1, c] \).

The interbank network \( B_B \) is taken directly from the interbank dataset. Data on bank-firm relationships is used to establish an unweighted bipartite network between firms and banks. This bipartite network is used as a basis for the \( BC \) and \( CB \) adjacency matrices, which are (after assigning weights, see below) combined with \( BB \) and padded.
with zeros to obtain the liability network \( L \). To match the interbank network \( BB \) with the bipartite bank-firm networks \( BC \) and \( CB \) the banks of both datasets were ranked according to total assets. The resulting tables were then joined with their rank as common column.

The weights of the bipartite liability network of firms and banks are assigned the following way:

- For every firm \( c \), we take the aggregated liabilities \( L_c \) the firm has toward banks from the balance sheet.
- We then take the set of aggregated loans (referred to as assets, or \( A_i \) where \( i \) is the index of a bank/firm) of all banks from their balance sheets and assign them to the entries of the vector \( \ell \) in the following way:
  \[
  \ell_b = \begin{cases} 
  0 & \text{if } L_{cb} = 0 \\
  A_b & \text{else}
  \end{cases}
  \]
- We normalize the resulting vector with the L1 norm,
  \[
  \hat{\ell} = \frac{\ell}{\sum_i |\ell_i|}.
  \]
- We partition the aggregated liabilities with the distribution \( \hat{\ell} \) to obtain the entries for the firm-bank network \( L_c = L_c \cdot \hat{\ell} \).

Note that we partition the liabilities of each firm to the banks to which it is connected to, according to the relative size of the banks.

### 4. The liability network of Austria

We use empirical data (see section 2) to reconstruct the liability network of Austria, as outlined in section 3. The resulting network with 52,980 nodes is visualized in fig. 4 and represents approximately 80.2\% of total liabilities towards banks of firms and all interbank liabilities. Bank nodes are represented by squares and firms by circles. Node size corresponds to the total assets held by each node. For the following analysis we chose the subgraph induced by the set of all 796 banks in the Austrian banking system and the 5,000 firms with the highest liabilities.

The degree distributions of the banks in the entire liability network and the interbank network are illustrated in figs. 5 and 6. The in- and out-degree distributions are depicted in fig. 5 for the entire liability network \( F \), and in fig. 6 for the interbank network \( B \). In figs. 5 and 6 the main plots show the whole range, the insets provide a finer resolution in the ranges with higher density.

Table 1 shows the undirected and unweighted global clustering coefficients \( \langle C_i \rangle \) of both networks and the global clustering coefficient of a random graph with same number of nodes and links. The random graph has considerably lower clustering as both networks.

| Network                  | Nodes | Links | \( \langle C_i \rangle \) | \( \langle C_i \rangle \)\text{rand} |
|-------------------------|-------|-------|-------------------------|-----------------------------|
| Entire network \( F \)  | 5,796 | 28,127| 0.77                    | 0.005                       |
| Interbank network \( B \)| 796   | 12,783| 0.89                    | 0.043                       |

Figure 4: Reconstructed liability network of Austria with 796 bank nodes ■ and 51,980 firm nodes ● in 2008. The network represents approximately 80.2\% of total liabilities towards banks of firms and all interbank liabilities. Node size corresponds to the total assets held by each node.
Figure 5: In- and out-degree of banks in the entire liability network $F$. Main plot has 60 uniform bins on the interval $[0, 3000]$, the inset shows the distribution of degrees in the range $[0, 100]$.

Figure 6: In- and out-degree of banks in the interbank network $B$. Main plot has 60 uniform bins on the interval $[0, 360]$, the inset shows the distribution of degrees in the range $[0, 100]$.
graphs with identical number of nodes and vertices \( (C_i)^{\text{rand}} \), as shown in table 1.

Figure 7 shows the degree distribution of firms in the entire liability network (similar to fig. 2. The degree distribution is restricted to firms with degree > 0 and contains the 5,000 firms with the highest liabilities in 2008. Note that the in- and out-degree for firms are identical, as the bank connections provided to the commercial register were used for both types of connections between firms and banks, deposits and liabilities.

5. Systemically important firms and banks in Austria

To identify systemically important firms and banks we use DebtRank. DebtRank was originally suggested as a recursive method to determine the systemic relevance of nodes within financial networks (Battiston et al., 2012). It is a quantity that measures the fraction of the total economic value \( V \) in the network that is potentially affected by the distress of an individual node \( i \), or by a set of nodes \( S \). For details see Appendix A.

Figure 8 shows all banks (squares) and firms (circles) with a DebtRank \( R_F^F \geq 0.01 \). Node size represents the total assets, whereas the color encodes the DebtRank. Nodes with the highest DebtRanks are typically large banks with substantial total assets, but there are also several nodes with a high DebtRank that represent medium-sized banks and firms. In particular, some medium-sized banks and firms with total assets below 1 bln. EUR exist that have a rather high DebtRank (\( \approx 0.4 \)).

This can also be seen in fig. 9, which shows the DebtRank values of firms and banks plotted against their total assets. In general, firms as well as banks with larger assets tend to have a higher DebtRank. However, firms with similar DebtRank have differences in their total assets of multiple orders of magnitude.

\[ \text{DebtRank } R_F^F \geq 0.01 \]

Figure 8: Subgraph of fig. 4 with nodes having a DebtRank \( R_F^F \geq 0.01 \). Bank nodes are represented by squares and firms by circles. Node size corresponds to the total assets held by each node. Nodes are colored according to their DebtRank. Nodes representing firms and banks with more assets tend to have a higher DebtRank, but there are also several nodes with a high DebtRank that represent medium-sized banks and firms.

Figure 9: DebtRank of firms and banks plotted against their total assets (as a proxy for firm size) in Euro. Firms with similar DebtRank have differences in their asset sizes of multiple orders of magnitude. Distribution of banks and firms do not seem to be qualitatively different.

\[ \text{DebtRank } R_F^F \geq 0.01 \]

\[ \text{Total assets (EUR)} \]

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\(^3\text{We used the network layout algorithm from Hu Yifan Hu (2006) implementation in Gephi Bastian et al. (2009) to create the network illustrations in this work.}\)
orders of magnitude. The distribution of banks and firms does not seem to be qualitatively different.

In fig. 10 we show firms and banks in Austria ranked according to their systemic importance measured by DebtRank. Figure 10 shows the 45 banks and firms with the highest DebtRanks, ranked by their DebtRank in decreasing order from left to right. With the exception of the three largest banks in Austria (see also fig. 8), the distribution of banks and firms does not seem to be qualitatively different. For example, the highest DebtRank of a firm in Austria is 0.39. Thus, a default of this firm would affect 39% of the Austrian financial system.

Figure 11 shows the 45 firms with the highest DebtRank and additionally provides information about their line of business, according to the first level of their OeNACE code (below the bars), a system to classify economic activities used in Austria Wirtschaftskammer Österreich (2008). Clearly, systemically important firms are found in various industries.

In fig. 12 the distribution of DebtRank values of firms and banks (inset) is depicted with a histogram (70 bins and range = [0, 0.7] in both cases). Again, banks and firms have a qualitatively similar DebtRank-distribution. Apparently, systemically important firms contribute systemic risk in a similar way as banks.

Finally, we estimate the share of systemic risk introduced by firms in the entire liability network. We define $Q_1$ as the ratio of the sum of the DebtRanks of all firms divided by the sum of all DebtRanks in the entire liability network,

$$Q_1 = \frac{\sum_{i \in F} R_i^F}{\sum_{i \in F} R_i^F}.$$ (2)

We find $Q_1 = 0.55$ in Austria for 2008. Firms introduce more than half of the systemic risk in the entire liability network network (more than banks). To compare the systemic risk of the interbank network with the systemic risk of the entire liability network we define a similar ratio

$$Q_2 = \frac{V^B \sum_{i \in B} R_i^B}{V^F \sum_{i \in F} R_i^F},$$ (3)

where $V^B$ and $V^F$ refer to the total economic values of the interbank network and the entire liability network, respectively. In this case we must take the different economic value of the two networks into account, since the DebtRank is a relative measure. We find $Q_2 = 0.29$ in Austria for 2008, i.e. the total systemic risk of the interbank network amounts to only 29% of the total systemic risk of the entire liability network.

6. Conclusions

Systemic importance of financial institutions is related to the topology of financial networks to a large extent. In this work we reconstruct and analyze the to our knowledge largest financial network that has been studied up to now. This financial network consists of 51,980 firms and 796 banks representing 80.2% of total liabilities towards banks by firms and all interbank liabilities from the entire Austrian banking system visualized in fig. 4.

We find that firms induce systemic risk in a similar way as banks. Banks and firms have a qualitatively similar distribution of systemic importance (see fig. 12). In particular, we identify several medium-sized banks and firms with total assets below 1 bln. EUR in Austria that are systemically important in the entire financial network. Systemic importance of these firms is primarily driven by their position in the network. Moreover, these firms belong to various industries (fig. 11). We further find that banks and firms of similar systemic importance have differences in their asset sizes of multiple orders of magnitude (fig. 9).

Our main result is that, overall, firms introduce slightly more systemic risk than banks and that in Austria for the year 2008 the total systemic risk of the interbank network amounts to only 29% of the total systemic risk of the entire financial network consisting of firms and banks.

These results come with three caveats due to partially missing and partly inaccurate data. First of all, the analyzed financial network is reconstructed and not directly taken from empirical data. However, the reconstruction process only involves reconstructing the weights from the (unweighted) adjacency matrix, which is directly taken from empirical data. Moreover, for a large subset of firms, the liabilities towards banks (42.4% of total liabilities towards banks) are known exactly and do not need to be reconstructed since these firms are only customers of one bank (fig. 2). The interbank liabilities are also not reconstructed. Second, interbank liabilities from the Austrian banking system are fully anonymized and linearly transformed. Thus, there is a small uncertainty in the absolute value of the interbank liabilities, which also introduces some uncertainty in the matching process of the various datasets and third, our analysis involves only one snapshot of the Austrian financial system in 2008 – the only year, where the necessary datasets overlap.

It would be interesting to extend this study to other countries and to investigate the evolution of similar large financial networks that consist of firms and banks and represent interbank liabilities and the liabilities towards banks by firms. It would further be interesting to go beyond the scope of this work and study a financial network that truly represents all liabilities between all economic agents from all sectors (households, non-financial and financial firms and the government sector) in an entire national economy.

Though further investigation might be necessary to confirm our findings for other countries and over longer time horizons, we believe that this contribution is a valuable first comprehensive quantification of the financial interrelationships between the financial and the real economy. We show that the notion of systemically important financial institutions (SIFIs) or global and domestic systemically important banks (G-SIBs or D-SIBs) can be straightfor-
Figure 10: DebtRanks of 45 firms and banks sorted by their DebtRank from left to right in decreasing order. With the exception of the three largest banks in Austria (see also fig. 8), the distribution of banks and firms does not seem to be qualitatively different.

Figure 11: Firms in different economic sectors ranked by DebtRank (in descending order). The colors correspond to the economic sector in which the firms operate, according to the first level of their OeNACE classification (also used as x-axis label).

Figure 12: Histogram of DebtRanks $R^F$ in the entire liability network of banks $R^B$ and firms $R^F$. Banks and firms have a qualitatively similar DebtRank-distribution. The highest DebtRank of a firm is 0.39.
wardly extended to firms. In particular, we identify several medium-sized banks and firms with total assets below 1 bln. EUR in Austria that are systemically important. In conclusion, our analysis suggests that not only systemically important financial institutions but also systemically important firms must be subject to macro-prudential regulation.

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wirtschaftly extended to firms. In particular, we identify several medium-sized banks and firms with total assets below 1 bln. EUR in Austria that are systemically important. In conclusion, our analysis suggests that not only systemically important financial institutions but also systemically important firms must be subject to macro-prudential regulation.

Acknowledgments

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Appendix A. DebtRank

The financial dependencies of the nodes in the network are given in a liability matrix $L$ with entries $L_{ij}$ denoting that node $j$ has given node $i$ a loan (or investment/deposit) of size $L_{ij}$. Additionally, there is a capital (or equity) vector $C$ with entries $C_i$ denoting the capital of node $i$.

The relative economic value of a node $i$ is given by

$$v_i = \frac{L_i}{\sum_j L_{ij}} \quad \text{(A.1)}$$

where $L_i = \sum_j L_{ij}$ is the sum of the outstanding liabilities of node $i$.

The default of node $i$ then affects all nodes $j$ where $L_{ij} > 0$. The impact of the default of $i$ on $j$ is defined as

$$W_{ij} = \min\left(\frac{L_{ij}}{C_j}, 1\right). \quad \text{(A.2)}$$

The impact of a shock is thus measured as the fraction of capital loss due to the credit default. It is therefore a value in the range $[0,1]$ with the semantics $W_{ij} = 0$ if the default of node $i$ does not affect node $j$, and $W_{ij} = 1$ if the default of node $i$ results in a loss that matches or exceeds the capital of node $j$.

The economic value of the impact of $i$ on its neighbors is therefore given by

$$I_i = \sum_j W_{ij}v_j \quad \text{(A.3)}$$

Though if the neighbors of $i$ do not have enough capital to compensate for the default of $i$, they default themselves, leading to an impact on their neighbors and reverberations in the network along paths in the impact network $W$. To prevent infinite cycles, Battiston et al. proposed to only take walks without repeating links. This is achieved by introducing two additional state variables for each node, $s_i$ and $h_i$ (both dependent on the time step $t$). The variable $s_i$ takes one of three values:

| $s_i(t)$ | Interpretation                      |
|----------|------------------------------------|
| U        | Node $i$ is undistressed at time $t$ |
| D        | Node $i$ is in distress at time $t$  |
| I        | Node $i$ is inactive at time $t$    |

The variable $h_i$ has a value in the range $[0,1]$ and is the level of distress, with 0 meaning undistressed and $h_i(t) = 1$ in the case of default. The value of $h_i(t)$ is defined as

$$h_i(t) = \min\left(1, h_i(t-1) + \sum_{j \mid s_j(t-1)=D} W_{ji}h_j(t_1)\right), \quad \text{(A.4)}$$

whereas $s_i(t)$ is given by:

$$s_i(t) = \begin{cases} D & \text{if } h_i(t) > 0 \land s_i(t-1) \neq I, \\ I & \text{if } s_i(t-1) = D, \\ s_i(t-1) & \text{otherwise} \end{cases} \quad \text{(A.5)}$$

To calculate the DebtRank of a node $d$ (d for defaulting), the distress $h_i$ and status $s_i$ at time step $t = 1$ are initialized as follows:

$$h_i(1) = \begin{cases} 1 & \text{if } i = d \\ 0 & \text{otherwise} \end{cases} \quad \text{(A.6)}$$

$$s_i(1) = \begin{cases} D & \text{if } i = d \\ U & \text{otherwise}. \end{cases} \quad \text{(A.7)}$$

Then the values of $s_i$ and $h_i$ are calculated for every node $i$ and time step $t$, according to eqs. (A.4) and (A.5) until all nodes are either inactive or undistressed at $t = T$. The DebtRank of node $d$ can then be calculated as the sum of the distress in the whole network at time $t = T$ reduced by the distress at the beginning, i.e. the initial distress of node $d$ at $t = 1$:

$$R_d = \sum_i h_i(T)v_i - h_d(1)v_d. \quad \text{(A.8)}$$

It would be possible to calculate the combined DebtRank of a set $S$ of simultaneously defaulting nodes by replacing the $i = d$ conditions in the initialization (eq. (A.7)) by $i \in S$ and changing eq. (A.8) to one of the following equations:

$$R_S = \sum_i h_i(T)v_i - \sum_{d \in S} h_d(1)v_d \quad \text{(A.9)}$$

$$R_S = \sum_i h_i(T)v_i. \quad \text{(A.10)}$$

Equation (A.9) excludes the impact of the initial shock, whereas eq. (A.10) does not.

In this work, DebtRank is calculated on two different networks, the interbank network $B$ and the entire liability network $F$. We use $R^B$ and $R^S$ to discern between the two measures.