DISCUSSION PAPER SERIES

DP17511

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ECONOMIC HISTORY

FINANCIAL ECONOMICS

CEPR

ISSN 0265-8003

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Discussion Paper DP17511
Published 28 July 2022
Submitted 21 July 2022

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JEL Classification: D85, E42, F30, G20, N20

Keywords: Financial Networks, systemic risk, hypergraphs, Intermediation chains, Bills of Exchange, hyperstructures

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Acknowledgements
For their comments on preliminary versions of this paper, we are grateful to Guillaume Favre, Michel Grossetti, Katia Jaffrès-Runser, Jérôme Vicente, as well as to participants at presentations in Aix-en-Provence, Geneva, Oxford, Paris, Toulouse, and Zurich. Financial support from Sciences Po Toulouse is gratefully acknowledged. The usual disclaimers apply.

Intermediaries' Substitutability and Financial Network Resilience: A Hyperstructure Approach*

Olivier Accominotti† Delio Lucena-Piquero‡ Stefano Ugolini§

This draft:

July 21, 2022

Abstract

We propose a new methodology to assess intermediaries' substitutability in financial networks featuring higher-order structures (credit intermediation chains). We represent the financial network as a *hyperstructure* and each credit intermediation chain as a *hyperedge*. This approach allows us to assess how the failure of intermediaries affects network connectivity. We apply this methodology to a unique dataset documenting the structure of the international, sterling money market at the heyday of the first globalization era (1880-1913). Our results reveal that the failure of individual money market actors could only cause limited damage to the network as intermediaries were highly substitutable. These findings suggest that an international financial network without highly systemic nodes can emerge even at a time of global economic integration.

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1. Introduction

Financial networks are prone to systemic risk. The global banking system is characterised by strong linkages between financial institutions. While global banking integration entails significant diversification benefits for banks, interconnections between financial institutions can also amplify and spread financial troubles as evidenced during the 2007-2009 Global Financial Crisis.

Over the last decades, scholars have demonstrated how the structure of relationships between banking institutions can affect the transmission of financial shocks (Allen and Gale, 2000; Freixas et al., 2000). Regulatory authorities have evolved from a microprudential approach focusing on the position of individual intermediaries to a macroprudential one where more attention is being paid to relational structures between banks (Basel Committee on Banking Supervision, 2013). Numerous studies have explored how links between banks are being formed and have analysed the importance of network structure for the resilience of financial systems (Allen and Babus, 2009; Glasserman and Young, 2016; Battiston and Martinez-Jaramillo, 2018; Caccioli et al., 2018; Iori and Mantegna, 2018). Empirical studies generally show that modern financial networks are characterised by the presence of a small group of highly-connected intermediaries whose failure can result in the breakdown of the entire system.[1] It would therefore appear that financial systems inevitably feature a few systemic actors and that they all share similar vulnerabilities.

Empirical evidence on financial networks is mostly based on data documenting bilateral relationships between financial institutions on individual countries' interbank markets. Only a few studies have analysed the network structure of international financial connections. In this paper, we study the resilience of a major historical, global financial network: the sterling money market during the first globalization era of 1880-1914. During this period, international goods and financial markets were as integrated as in the late twentieth century (O'Rourke and Williamson, 2002). The City of London was the centre of the global financial system and its money market – the market for sterling bills of exchange – served as a global

[1] See for example, Craig and Von Peter (2014), Boss et al. (2004), Upper and Worms (2004), Müller (2006), Wetherilt et al. (2010), Soramäki et al. (2007), Minoiu and Reyes (2013), Chinazzi et al. (2013), Fricke and Lux (2015a).

platform for short-term international lending and borrowing (Accominotti and Ugolini, 2020). Firms located anywhere in the world used that market to obtain short-term funds from financial institutions, with the guarantee of a London-based intermediary.

Our analysis is based on an original dataset of financial interlinkages between actors active on the London money market during the year 1906, which we assembled from archival sources. The dataset contains systematic micro-level information on the 23,493 bills of exchange re-discounted by the Bank of England in 1906 and on all actors involved in their origination and distribution (see Accominotti et al., 2021). Given the still opaque nature of most interbank connections today, empirical financial network research is often based on estimated rather than observed data. Relationships between banks are typically inferred from balance sheet or payments data (Furfine, 1999; Upper and Worms, 2004; Allen and Babus, 2009; Upper, 2011). Although researchers have produced interesting results based on estimated data, several scholars have also questioned the reliability of this method (Upper, 2011; Mistrulli, 2011; Anand et al., 2018).[2] One advantage of our historical database is that it is solely based on observed and systematically recorded links between money market participants. Our approach therefore does not require making any assumption to reconstruct interactions between money market actors.

Our dataset on the sterling money market in 1906 contains information on both bank-bank and bank-firm relationships. Every bill of exchange transaction on the money market involved three different actors: a.) a borrowing firm located anywhere in the world (borrower); b.) a London-based intermediary which guaranteed that firm's debt (guarantor); and c.) a bank or money market fund that lent cash to the borrowing firm (lender). Therefore, each transaction embraced both a "firm-bank" (borrower-guarantor) relationship and a "bank-bank" (guarantor-lender) relationship. Since each bill of exchange recorded the names of the borrower, guarantor and lender in the underlying transaction, we can reconstitute the precise nature of interlinkages between actors on the bill market.

[2] The Italian interbank network is one of the only networks for which complete transaction data have been available. See Iori et al. (2008), Fricke and Lux (2015b), Iori et al. (2015), and Temizsoy et al. (2015).

While banking network research is generally based on the analysis of dyadic relationships, network science scholars have also stressed how this approach can be misleading when transactions involve more than two actors (Bonacich et al., 2004; Estrada and Rodríguez-Velázquez, 2006; Battiston et al., 2020; Bianconi, 2021). To analyse the many-body interactions typical of complex systems, authors have recommended modelling these systems as higher-order interaction networks. We follow this approach here and analyse "firm-bank-bank" interactions in the money market network using the concepts of *hypergraph* and *hyperstructure*. We represent the entire set of money market actors as a *hyperstructure* (an association between adjacency and incidence matrices). We describe each sterling bill of exchange as a continuous intermediation chain or the *hyperedge* of a *hypergraph* that connects three different nodes, each playing one of the three roles (borrower, guarantor or lender) in the underlying credit transaction. This *hyperstructure* approach allows us to preserve each chain's internal structure and unity (Criado et al., 2010; Lucena-Piquero et al., 2022). We propose a new method using a meso-level approach to analyse directed links between nodes within each intermediation chain. One advantage of this approach is that it allows us to consider the *gatekeeping* or *bridging* role that certain intermediaries play on the money market (Bonacich et al., 2004). For example, a bank can be considered a gatekeeper or bridge if it lends to a firm and, then, refinances itself by borrowing from another financial intermediary on the money market. Similarly, intermediaries which guaranteed borrowers' debts in order to allow them to borrow from other financial institutions, acted as gatekeepers or bridges on the London money market.

We use simple simulation techniques in order to assess the systemicness of actors on the money market and draw implications for the resilience of the system. Our main focus is on financial institutions' *substitutability*.[3] Hence, we assess network disruptions by looking at the number of actors that would lose market access if specific intermediaries were removed from the network. Our results provide an upper-

[3] In 2013, the Basel Committee on Banking Supervision (2013) and the Financial Stability Board (FSB) jointly published new guidelines for the assessment of banks' systemicness. The guidelines distinguished between five dimensions of systemicness: 1. *size* (total size of the bank's liabilities); 2. *interconnectedness* (network of contractual obligations which characterise the bank's activities); 3. *substitutability* (the bank's importance as a provider of client services); 4. *complexity* (business, structural, and operational complexity of the bank including its involvement in sophisticated activities such as derivatives or other off-balance-sheet exposures); and 5. *cross-jurisdictional activity* (geographical dispersion of the bank's activities). Assessing substitutability has proved particularly difficult (Benoit et al., 2019), leading regulators to revise their guidelines on this aspect of systemicness (Basel Committee on Banking Supervision, 2018).

bound estimate of network fragility, as our methodology rests on the restrictive assumption that no other financial relationship between actors can be formed besides those actually observed. In other words, we assume that existing financial relationships cannot be replaced, so that an agent loses market access when the intermediaries to whom she is currently connected default. When applying this methodology to modern interbank markets, one typically finds that a few nodes are non-substitutable as removing them results in a complete breakdown of the network (Pröpper et al., 2008).

Our main finding is that systemic risk in the sterling money market was remarkably low at the beginning of the twentieth century. We find that the money market network was resilient even to the removal of central nodes. Although our assessment of intermediaries' systemicness constitutes an upper-bound estimate, we find that no single intermediary on the money market was highly systemic. Any node removal could only generate limited damage to the network. The network's various subsections were also all robust to the removal of individual nodes as very few agents were strictly dependent on individual nodes for their money market access. Our data also allows documenting the location of money market borrowers at the city level. We study the network's geographical systemicness and find that very few cities across the world would have been cut off from the market had individual nodes been removed. Therefore, in contrast to findings obtained on modern banking networks, our analysis of the historical sterling bill market reveals that an international financial network featuring low systemicness could emerge even during a period of high global economic and financial integration.

Our paper contributes to the empirical literature on financial network structure. Empirical studies of modern financial systems have generally found that these networks exhibit a strong *core-periphery* structure (sometimes referred to as a *scale-free* structure)[4] with a small group of highly-connected actors centralizing flows and playing the role of hubs (Craig and Von Peter, 2014). This structure, which can be identified by looking at several indicators such as the network's *degree distribution*,[5] has important implications for the

[4] In theory, *core-periphery* and *scale-free* structures are not exactly equivalent. It is however difficult to distinguish between the two types of structures in empirical investigations (Iori and Mantegna, 2018, p. 645).

[5] The distribution of the nodes' degrees in a network defines its *hierarchy*. A network is hierarchical if a small number of nodes have a significantly higher degree than most other nodes in the network.

vulnerability of financial systems. While core-periphery structures are generally robust to shocks on random individual actors, they become very fragile when these shocks affect actors who are playing the role of hub (Albert et al., 2000; Newman, 2003). This characteristic is known as the *robust-yet-fragile* property of financial networks (Gai and Kapadia, 2010). The presence of a hierarchical structure appears to be a common feature of all modern interbank networks and has been recently described as "a new 'stylized fact'" (Fricke and Lux, 2015a, p. 391).[6] Our paper however provides evidence that alternative network structures can also emerge. We describe how a major historical financial network was characterised by the absence of highly systemic hubs. While the money market network we study exhibits a structure that in certain respects resembles that of scale-free networks, it also displays much stronger resilience to shocks than these typical networks.

Our paper also makes a methodological contribution. While most studies of financial networks have focused on interactions between financial intermediaries (bank-bank networks), a handful of papers have also analysed bank-firm links alongside bank-bank links (De Masi et al., 2011; De Masi and Gallegati, 2012; Lux, 2016; Silva et al., 2018). These studies have however represented bank-bank and bank-firm relationships as different types of dyadic links within a multilayer network and have therefore treated the two types of relationships as different (albeit interconnected) networks. By contrast, our approach, which consists in analysing interactions within chains of actors, allows us to model bank-bank-firm relationships as part of a single, higher-order network. While hypergraphs have been used before in network science, our paper is the first to our knowledge to apply this approach to financial networks. It is also the first to our knowledge to model the direction of links between nodes in a hyperstructure. This approach allows us to preserve the chains' internal configuration and unity and explore how the failure of various types of intermediaries could impact actors' access to the money market. The methodology we develop here

[6] The core-periphery structure has been identified empirically in the case of various countries' domestic interbank networks such as Austria (Boss et al., 2004), Belgium (Degryse and Gregory, 2004), Germany (Upper and Worms, 2004), Switzerland (Sheldon and Maurer, 1998; Müller, 2006), the United Kingdom (Wetherilt et al., 2010), or the United States (Soramäki et al., 2007), as well as for country-to-country networks (Minoiu and Reyes, 2013; Chinazzi et al., 2013). Only a minority of empirical studies have found evidence of less hierarchical structures with a weaker core-periphery structure. This is the case of the domestic interbank networks of Italy (Iori et al., 2008; Fricke and Lux, 2015b), the Netherlands (Blasques et al., 2015), and Mexico (Martinez-Jaramillo et al., 2014).

constitutes an important contribution and could be adapted to study the resilience of other directed networks characterised by the presence of chains of actors such as, for example, global supply chains (Lucena-Piquero et al., 2022). Finally, our paper also contributes to the literature on the modern international banking network (Espinosa-Vega and Solé, 2010; Minoiu and Reyes, 2013; Chinazzi et al., 2013; Minoiu et al., 2015; Hale et al., 2016; Cai et al., 2018).

The remainder of the paper is organised as follows. Section 2 describes our data and details our empirical strategy. Section 3 presents descriptive statistics on the structure of the sterling money market network. Section 4 presents our main results on intermediaries' substitutability as well as several robustness checks. Section 5 concludes.

2. Data and methodology

2.1. Data

Our empirical analysis is based on an original dataset of international financial interlinkages during the first globalization (1880-1914). At that time, London was the unrivalled global financial centre and the sterling-denominated *bill of exchange* was the staple international money market instrument (Accominotti and Ugolini, 2020). Our dataset was hand-collected from one archival source (the Bank of England's *Discount Ledgers*) and includes information on 23,493 bills of exchange issued on the sterling money market and discounted by the Bank of England during the calendar year 1906. A detailed discussion of the nature and representativeness of these data can be found in our historical companion paper (Accominotti et al., 2021).[7]

Figure 1 here

[7] The sterling bill market was an over-the-counter market and no systematic information was collected on transactions taking place on that market. However, archival records allow reconstituting all relationships between actors involved in the origination and distribution of bills purchased (re-discounted) by the Bank of England. Bills rediscounted by the Bank of England represented only a small minority of all sterling bills issued. However, Accominotti et al. (2021) perform a series of cross-checks and conclude that these bills were fairly representative of the whole market.

The market for sterling bills of exchange was the world's dominant money market in the early twentieth century. As illustrated in Figure 1, any sterling bill transaction involved three actors: a borrower (called the *drawer*, a firm), a guarantor (called the *acceptor*, an intermediary), and a lender (called the *discounter*, generally a bank or money market fund). Borrowing firms located anywhere in the world and willing to obtain short-term sterling funds could draw a bill on a London-based intermediary (an *acceptor*) with whom they had a relationship. The intermediary accepted the bill by putting its signature on it and, in so doing, agreed to repay the bill at maturity (typically, after three months) in the expectation that it would itself have received payment from the borrower in the meantime. After obtaining the signature/guarantee of an intermediary (*acceptor*), the borrower (*drawer*) could discount the bill to a UK financial institution willing to lend funds on the money market (the *discounter*). For each sterling bill originated, our archival source provides information on the identity of the borrower, guarantor and lender. We are therefore able to document all borrower-guarantor ("firm-bank") and guarantor-lender ("bank-bank") relationships and reconstruct the complete network of interlinkages between agents operating on the money market. Our static network for the year 1906 contains 4,970 nodes, 1,680 (33.80%) of which were located in London. The other nodes consisted of borrowing firms spread across the entire world.

2.2. Hyperstructure

Given the systematic presence of an intermediary (guarantor) between the borrower and lender in any money market transaction, a simple network composed of pairwise relationships cannot account for the complexity of interactions on that market. We therefore rely on network concepts and models recently developed to analyse complex systems (Bonacich et al., 2004; Estrada and Rodríguez-Velázquez, 2006; Battiston et al. 2020). To describe the three-role interactions between actors and preserve the integrity of each borrower-guarantor-lender relationship, we depart from the standard dyadic-based graph and represent the money market as a higher-order network. We analyse relationships between agents involved in a sterling bill transaction using the concept of *hyperstructure*.

Following Criado et al. (2010), we define a *hyperstructure* as a combination of an *adjacency matrix* (a matrix recording the presence or absence of a dyadic link between each pair of nodes) and an *incidence matrix* (a matrix recording the hyperedges to which each node belongs). To present their intuition, Criado et al. (2010) give the example of a subway network. Such a network is composed of a set of subway stations (the nodes) and a set of trunks connecting pairs of stations (the edges). Stations and trunks are grouped into subway lines (the hyperedges). A passenger travelling between two stations separated by the same number of trunks will face substantially different situations if these two stations are located on the same line or if they are on two different lines. For instance, if each subway ticket is valid on one line only, interchange will not be an option, and a passenger holding a ticket will only be able to reach stations located on the corresponding line. Similarly, a money market borrower might only be able to reach a given lender via certain credit intermediation chains. While the standard dyadic approach does not allow accounting for these differences, hyperstructures do. Our analysis builds on Criado et al. (2010)'s intuition and extends it to analyse non-symmetrical (directed) relationships within hyperstructures.

More formally, let us represent the money market network as a finite set of individuals $V = \{i_1, i_2, i_3 \dots i_n\}$. Each bill can be represented as a chain $C_k \in \{C_1, C_2, C_3 \dots C_m\}$, defined as a non-empty set $\{a, b, c\} \in V$ in which there exist both a borrower-guarantor relationship (aTb) and a guarantor-lender relationship (bUc) so that $C_k = (aTbUc)\ \forall \{a, b, c\} \in V \wedge \{T, U\} \in R$, where: a, b, and c indicate the roles of (respectively) borrower, guarantor, and lender; T and U indicate (respectively) the borrower-guarantor and guarantor-lender relationship; and R is the full set of relationships in the network. For any node i, we indicate the chains to which i belongs as $C_k^i = (aTbUc)\ \forall \{a, b, c\} \in V \wedge i \in \{a, b, c\}$.[8] We represent the network of chains as a hypergraph $H = (V, E)$: $\forall\ C_k\ \exists\ E_k$, where $E_k \in \{E_1, E_2, E_3 \dots E_m\}$ is a set of hyperedges. Our hyperstructure S will therefore be composed of the chains C_k (each of which associates three linked nodes $(a, b, c) \wedge i \in \{a, b, c\}$) *and* of the hyperedges E_k that integrate them.

[8] Note that nodes' specialization was not absolute. Each actor could play different roles in the various transactions in which it was involved. In our data, however, such nodes playing more than one role are relatively rare.

Representing the entire set of chains as a hyperstructure allows preserving these chains' unity (captured by their affiliation to a given hyperedge) and the specific ordering of nodes within each of them (captured by the dyadic links between nodes). In addition, the concept of hyperstructure provides a flexible analytical framework and allows characterising networks' structural properties through simple social network measures such as, for example, degree centrality measures.

2.3. Shock simulations

In order to measure the resilience of the money market network to shocks, we perform a simple node removal simulation analysis.[9] While different types of financial contagion have been identified in the literature, we focus specifically on default contagion (Battiston and Martinez-Jaramillo, 2018).[10] We adopt a straightforward approach for our shock simulations, which consists in measuring the damage caused by node removals (defaults) to network connectivity.[11]

More precisely, in any chain of the network, there is one node situated in position 1 (borrower), one node situated in position 2 (guarantor) and one node situated in position 3 (lender). We simulate the removal of individual nodes situated in position 2 or 3 of each chain (and thus playing the role of either guarantor or lender) and assess how many actors would lose market access in case of their removal. A given node i's structural relevance is therefore measured through the number of money market actors that are strictly dependent on i for their market access. A node is considered independent from i if it is

[9] Following Allen and Gale (2000), shock simulations have become a standard method to analyse default cascades within financial networks (Gai and Kapadia, 2010).

[10] Battiston and Martinez-Jaramillo (2018, pp. 7-8) identify four types of contagion in financial network: default contagion, distress contagion, common assets contagion, and funding liquidity contagion. In this paper, we are interested in understanding how dependent various actors were on specific intermediaries for their money market access and we therefore focus on default contagion.

[11] An alternative method consists in modelling default cascades as a function of interbank exposure. In that case, each node receives a shock from its incoming links and spreads it to its outcoming links. In these types of simulations, the effect of one bank's default on another bank is generally assumed to be proportional to the bilateral exposure between the two banks (Eisenberg and Noe, 2001; Müller, 2006; Battiston et al., 2012a, 2012b; Acemoglu et al., 2015; Glasserman and Young, 2015). This approach requires obtaining information on the magnitude of bilateral interbank exposures or to reconstruct this information based on partial data. Our data do not allow us to construct weighted links between nodes in the network. We therefore opt for a simpler node removal approach. This method has been used extensively in network analysis (Albert et al., 2000; Newman, 2003; Cohen and Havlin, 2010; Li et al., 2015) and has also been applied to financial networks (Pröpper et al., 2008). One advantage of this method compared to the *fictitious default algorithm* initially developed by Eisenberg and Noe (2001) is that it does not require making any assumption about how shocks propagate from bank to bank (Allen and Babus, 2009; Upper, 2011).

connected to other nodes that can grant it market access; or, in other words, if it has access to other paths allowing it to participate into a full borrower-guarantor-lender chain. The number of nodes losing market access when i is removed is an indicator of i's degree of substitutability.

Figure 2 here

The hypothetical example presented in Figure 2 illustrates our methodology. The figure represents four different chains corresponding to groups of agents involved in four different bills of exchange: (A,B,C), (D,B,C), (D,B,F), and (D,E,F). Each chain involves a borrower (in position 1), a guarantor (in position 2) and a lender (in position 3). For example, in the chain (A,B,C), A plays the role of borrower, B the role of guarantor and C the role of lender. Each combination of two same-coloured arrows constitutes a hyperedge that integrates the three nodes and their links included in the corresponding chain.

Let us now suppose that node C (a lender) defaults and is removed from the network. This would result in the suppression of chains (A, B, C) and (D, B, C). As a result, node A (a borrower) would remain isolated and be cut off the money market as the only path through which that node can access a lender is path (A, B, C). By contrast, node D (another borrower) would still be able to borrow from the money market even if lender C defaulted as there exist two alternative paths (D, B, F) and (D, E, F) connecting that borrower to another lender (node F). This example illustrates the importance of preserving the integrity of observed chains when performing our shock simulation analysis. Ignoring the compound nature of relationships in the network would lead us to erroneous conclusions about the impact of individual node removals. For example, a standard dyadic approach would have led us to conclude that the suppression of node C has no impact on node A's connectivity. This would have been inaccurate as there exists in reality no chain (A, B, F) that could connect borrower A to the other lender (node F) in the network.

When simulating the impact of a given node i's removal, we first identify all chains in which i plays the role of guarantor or lender and single out all nodes involved in these chains (the reference set). We then check whether these individual nodes are involved in other chains in the network. If an individual node j is present in at least one other chain that does *not* involve i, it means that an alternative path exists allowing j to access the money market even in the absence of i; in other words, j is not strictly dependent on i for its market access. By contrast, if all chains to which node j belongs also include node i, then j loses market access and becomes isolated when i is removed. Formally, consider a node $i \in (bUc)$ of the chain $C_k^i = (aTbUc)$. Any node $j \in C_k^i \wedge\ j \neq i$ has an alternative access to the money market if $\exists C_k^j : i \notin C_k^j \wedge j \in C_k^i$.

Our methodology assumes that an actor remaining isolated as a consequence of another node's removal cannot build new, alternative paths to access the market. This assumption leads us to bias our results towards finding higher systemicness for lenders and guarantors, and against our hypothesis that the sterling money market network featured few highly systemic intermediaries.

3. Descriptive statistics

3.1. Network demography

In this section, we provide descriptive statistics to characterise the money market network's topology. We start with its demography. On the sterling bill market, borrowers (bill drawers) could be located anywhere in the world while it was a legal requirement for guarantors (bill acceptors) and lenders (bill discounters) to reside in London.

Table 1 here

Intermediaries were most often specialized in one of these three roles, but a few agents were *hybrid*, i.e., they played different roles in the different bills in which they were involved. Table 1 shows the distribution of money market actors according to their role and location. Borrowers were by far the most numerous group, followed by guarantors and lenders.[12] While a large majority of borrowers (61.71%) appear in one single chain of the network, this is only the case of 40.47% of the guarantors and of 17.93% of the lenders. This distribution resembles a funnel-shaped structure in which the number of potential individuals playing a given role is reduced at every stage of the transaction.

3.2. Network topology: method

To describe the network's topology, we follow the standard approach consisting in measuring its *node degree distribution* and in comparing it with that of *null* models, expressly simulated to display specific properties (Craig and Von Peter, 2014; Martinez-Jaramillo et al., 2014). We compare the node degree distribution of the observed network to that of 250 simulated *random* (Erdös-Renyi) networks and 250 simulated *scale-free* networks, each displaying the same number of nodes and hyperedges (and, thus, the same number of agents and chains) as the observed network. To ensure comparability, we constrain our simulations so that each individual borrower in simulated networks appears in the same number of chains as in the observed network. We also ensure that the simulated and observed networks feature the same number of borrowers, guarantors and lenders.

In a random network, every group of three nodes has the exact same probability of being connected through a hyperedge. Comparing the observed network's topology with that of simulated random networks allows assessing whether link creation in the observed network is guided by any kind of non-random relational dynamics (Iori et al., 2015; Chinazzi et al., 2013). In a scale-free network, by contrast, link creation is governed by a specific process known as *preferential attachment dynamics*. When simulating scale-free networks, we assume that individual actors have a greater tendency to establish links with well-connected nodes than with weakly-connected ones. This relational dynamic is conducive to the core-periphery network structure characteristic of most modern interbank systems (Martinez-Jaramillo et al., 2014; Iori and Mantegna, 2018). Applied to our network, this structure would involve that a large number of

[12] Note that the lenders (or discounters) in our dataset were mainly financial institutions (commercial banks, investment banks, money market funds) which purchased bills of exchange and re-sold them to other investors. They were therefore wholesale lenders and played an intermediary role on the money market (Accominotti et al., 2021).

borrowers (forming the network's periphery) are connected to a small number of lenders (forming the network's core) through the intermediation of guarantors. Simulated scale-free networks provide a useful baseline to assess whether the sterling money market exhibited such a topology.

3.3. Network topology: metrics

We compare nodes' degree centralities in the observed and simulated networks. In a hypergraph, a node will be considered central if it has many hyperedges (i.e. belongs to a large number of chains) and/or if it is connected to many other actors through its hyperedges (Kapoor et al., 2013; Battiston et al., 2020). Any hyperedge (or chain) to which a given node belongs is said to be *incident* to that node. All nodes sharing a same hyperedge (belonging to a same chain) are said to be *hyperedge-adjacent*. Hence, we define a node i's degree centrality in terms of:

1) its *in-degree* Id_i: the number of nodes to which it is connected through an input-arc (i.e., an incoming link):[13]

$$Id_i = \sum_{i,j=i_1}^{i_n} |\{(j,i) \in R\}| \; \forall \; \{i,j\} \in V$$

2) its *hyperedge degree* Hd_i: the number of its incident hyperedges (i.e., the number of chains to which it belongs):

$$Hd_i = \left|\{C_k^i \in E \, : \, i \in C_k^i\}\right| \; \forall \; C_k^i \in E$$

3) and its *hyperedge-adjacent nodes degree* $HANd_i$: the number of its hyperedge-adjacent nodes (i.e., the number of actors to which node i is linked through a hyperedge):

$$HANd_i = |\left\{\{j \in E_k^i : j \in V\}\backslash\{i\}\right\}| \; \forall \; E_k^i \, : \, i \in E_k^i$$

[13] By construction, a node playing the role of borrower in all its chains is always situated at the beginning of these chains and has an in-degree of zero.

The hypothetical example presented in Figure 2 can be used to illustrate the three network degree centrality metrics. In the case of node B in Figure 2 (a guarantor), $Id_B = 2$ (B is connected with two different nodes, A and D, by incoming links), $Hd_B = 3$ (B has three incident hyperedges or, in other words, belongs to three different chains), and $HANd_B = 4$ (B is connected to four different actors through its hyperedges). For the six nodes represented in Figure 2, Table 2 reports the value of each of the three network degree centrality metrics.

Table 2 here

3.4. Network topology: evidence

Using the three above-defined degree metrics, we now compare the topology of the observed network to that of simulated benchmark networks. For each of the three metrics, Figure 3 shows the degree distribution of the observed network versus that of the 250 simulated random networks and of the 250 simulated scale-free networks. The observed network's degree distributions significantly differ from those of simulated random networks. Therefore, we can rule out that link creation between actors on the money market followed a random or near-random process. At the same time, the observed network's nodes degree distributions look much closer to those of simulated scale-free networks.[14] While the large majority of nodes only appear in a small number of chains and are connected to a few actors only, the network also contains a very small number of intermediaries (lenders and guarantors) that appear in a very large number of chains and are connected to many other nodes through these chains.

[14] Note that the distribution of $HANd_i$ is significantly different in the observed and simulated networks. This is because, by construction, in simulated networks, $HANd_i$ tends to mostly take even values. In random networks, the probability that a link is formed is equal for each pair of nodes. Hence, a given actor is unlikely to be connected to the same node through more than one chain. As a result, actors will tend to be connected to twice as many nodes as the number of chains to which they belong. For example, any actor belonging to one single chain will be connected to exactly two nodes while most actors belonging to two different chains will be connected to exactly four other nodes. In scale-free networks, by construction, a large majority of nodes have a very low degree value and those actors are unlikely to belong to two different chains featuring the same nodes. Only the small minority of actors exhibiting high degree values are likely to be connected to a given node through more than one chain and to exhibit an odd $HANd_i$ value.

Figure 3 and Table 3 here

Despite apparent similarities in degree distributions, the observed network differs from the scale-free model in that its degree distribution is lighter-tailed. Table 3 shows that the most central node exhibits lower degree centrality in the observed network than in simulated, scale-free networks. For each of the three degree metrics, the table reports descriptive statistics on the maximum degree values in the 250 simulated random networks and 250 scale-free networks, and compares them with the maximum degree value in the observed network. The results indicate that simulated random networks did not feature any node that was as central as the observed network's most central node. However, in all but one of the 250 simulated scale-free networks, the maximum values of Id_i, Hd_i and $HANd_i$ are greater than the corresponding maximum values in the observed network. Therefore, the observed money market network does not feature as highly central nodes (so-called mega-hubs) as typical scale-free networks.

4. Results

4.1. Absolute and local systemicness

We now explore the resilience of the sterling money market network through a more detailed analysis of actors' systemicness. In order to assess the *absolute systemicness* of money market intermediaries (i.e., nodes playing the role of guarantor or lender), we perform shock simulations and remove them one by one from the network. We then identify the chains impacted and count how many nodes remain isolated from the network when a given intermediary is removed. We define a node i's *absolute systemicness* AS_i as the percentage of the total number of nodes that lose market access when i is removed. We also compare each node's AS_i to its *market share* MS_i, defined as the percentage of nodes in the network which belong to a hyperedge in which i is present (i.e., the percentage of nodes which are hyperedge-adjacent to i). The formal definitions of AS_i and MS_i are provided in Algorithm 1.

Algorithm 1 here and Table 4 here

In Table 4, we first compare the maximum values of absolute systemicness ($\max(AS_i)$) and market share ($\max(MS_i)$) in the observed network and in the simulated random and scale-free networks. For each of the two variables, the maximum value is higher in the observed network than in any of the 250 simulated random networks but lower than in any of the 250 simulated scale-free networks. This indicates that all simulated scale-free networks featured at least one node that was more systemic than the observed network's most systemic node. Interestingly, the ratio between the median $\max(AS_i)$ and median $\max(MS_i)$ appears to be higher for simulated networks than for the observed one. This invites a more detailed analysis of the actual distribution of AS_i and MS_i in the different networks.

Figure 4 here

Figure 4 presents a scatter plot of the two variables for all actors playing the role of guarantor and/or lender on the money market. We report the comparison for nodes in the observed network as well as in one representative simulated random network and one representative simulated scale-free network.[15] Two main features emerge from the figure. First, AS_i is low for all individual actors i in the observed network. Out of the 1,535 actors playing the role of guarantor or lender in the observed network, there are only two whose removal impacts more than 4% of market participants.[16] At the other end of the spectrum, 597

[15] These two representative simulated networks have been generated using the same procedure as for the previous 250 random and 250 scale-free networks. In the representative random network, $\max(Id_i)$=81, $\max(Hd_i)$=105, and $\max(HANd_i)$=196; in the representative scale-free network, $\max(Id_i)$=1,667, $\max(Hd_i)$=3,334, and $\max(HANd_i)$=2,200: compare this with mean and median values in Table 3. In the representative random network, $\max(AS_i)$=0.543 and $\max(MS_i)$=3.219; in the representative scale-free network, $\max(AS_i)$=26.685 and $\max(MS_i)$=43.514: compare this with mean and median values in Table 4.

[16] These two actors are Union Discount Company (7.83%), a large money market fund of the City of London at the beginning of the twentieth century, and Anglo-Foreign Banking Corporation (5.41%), a commercial bank specialised in foreign lending through its activities as guarantor and lender for overseas firms and banks.

actors have no impact at all. Second, AS_i rises less than proportionately with MS_i. Actors are situated on the 45-degree line on the figure when their removal impacts 100% of their hyperedge-adjacent nodes. Thus, the further to the right intermediaries are from the 45-degree line, the less dependent other nodes are on them for their market access. The figure reveals that the most central nodes in the observed network are situated well below the 45-degree line. This means that even the most highly systemic nodes in the observed network were relatively substitutable as few actors depended exclusively on them for accessing money market facilities. By contrast, in the simulated scale-free network, nodes with a high AS are also situated closer to the 45-degree line indicating that they are much less substitutable. Overall, these results indicate that the observed money market network featured less systemic actors than corresponding scale-free networks with the same demography.

Figure 5 here

For each node i, we also measure its *local systemicness* $LS_i = AS_i/MS_i$, i.e., the share of i's hyperedge-adjacent nodes which lose market access when i is removed (see Algorithm 1). Figure 5 plots the frequency distribution of LS_i across all nodes playing the role of guarantor and all nodes playing the role of lender in the observed network. A large number of guarantors exhibit intermediate levels of local systemicness. For 48.64% of guarantors, LS_i is situated between 20% and 50%. By contrast, only 36.55% of lenders display such intermediate levels of local systemicness and 17.24% of them exhibit a LS_i higher than 50%.[17] Overall, these results shed light on the differences between various types of intermediaries on the money market. While lenders displayed on average higher absolute systemicness than guarantors, they exhibited relatively lower levels of local systemicness.

Algorithm 2 here

[17] Note that these locally-systemic lenders were small on average. The mean and median hyperedge degrees Hd_i are equal to 6.36 and 2.00, respectively, for the 25 lenders whose local systemicness LS_i is greater than 50%.

While the removal of individual nodes could not cause significant damage to the network, the cumulative default of the most systemic intermediaries might nonetheless have led to its rapid breakdown. Removing any actor from the network results in the disappearance of all chains in which it is involved. To estimate the damage potentially caused by cumulative defaults, we present a measure of *spare-chain connectivity* obtained by sequentially removing nodes from the network in the order of their absolute systemicness (AS_i). Figure 6 reports the percentage of chains C_k of the original observed network that are preserved following the sequential removal of various numbers of nodes. Algorithm 2 formally details this procedure. We also compare how the sequential removal of systemic nodes affects the number of chains in the observed network versus in a simulated random network and a simulated scale-free network.

Figure 6 here

Removing the four most systemic nodes altogether from the observed network results in the disappearance of 26.7% of its chains. The observed network still conserves 49.6% of its original chains after the ten most systemic actors are removed and 6.9% after the removal of the fifty most systemic intermediaries. By contrast, the removal of the four most systemic nodes from the simulated scale-free network leads to the disappearance of as many as 82.9% of its chains and this network breaks down completely after the seven most systemic actors are removed. The random network is (unsurprisingly) much more resilient to the removal of its most systemic nodes than both the observed and scale-free networks. However, while the random network collapses completely following the removal of its 158 most systemic nodes, it takes the removal of 1,421 nodes for the observed network's chains to all disappear. This pattern indicates the presence on the money market of a significant number of intermediation chains featuring agents weakly connected to the rest of the network.

Overall, these results indicate that the sterling money market network was much more resilient to shocks than typical scale-free networks. It is also worth noting that, as stated above, our shock simulation methodology assumes that money market actors cannot build alternative paths to access the money market when the chains in which they are involved disappear. This assumption leads us to overestimate individual nodes' systemicness. Despite this upwards bias however, we find that the money market network was not subject to the *robust-yet-fragile* feature characteristic of most modern interbank networks (Gai and Kapadia, 2010). In the remainder of this section, we perform a number of robustness checks to corroborate this finding.

4.2. Sampling bias

The entire set of links within a financial network is rarely observable in full. Our historical dataset records information on a large, representative sample of sterling money market transactions for the year 1906 and documents all links between actors involved in these transactions. Yet, given the over-the-counter nature of money market dealings, not all transactions were being recorded and links between money market actors are therefore not all observable. Using incomplete data to infer the structure of a true network can result in sampling biases as recently emphasized by the literature on ecosystems (Fründ et al., 2016; Henriksen et al., 2018). How do these sampling effects affect our conclusions about systemic risk on the sterling money market?

In the absence of complete data, empirical network analysis is often based on a random sample of nodes drawn from the true network. This method can however lead to underestimate the true network's resilience as highly systemic nodes are generally very few and the likelihood of randomly selecting them is therefore low (Stumpf et al., 2005). By contrast, our observed money market network was built from a sample of bills of exchange (money market transactions) each involving three different nodes. In other words, the network was constructed from the sampling of chains rather than nodes. Since highly systemic nodes are by definition present in a large number of chains, the likelihood of selecting those nodes is much higher when the network is constructed from a sample of chains than from a sample of nodes. Hence, it is plausible that our sampling method leads us to overestimate rather than underestimate the true money market network's resilience to shocks.

Figure 7 here

In order to verify this intuition, we perform two types of checks. We first assess how maximum absolute systemicness in the observed network evolves with sample size. We randomly-select subsections of our observed network of various sizes and compute for each of them $\max(AS_i)$ – i.e., the absolute systemicness of the most systemic node in the network. We start with a sample that consists of 1,000 chains randomly selected from the observed network. We then add 1,000 additional (randomly-selected) chains to the previous sample and repeat this procedure until all chains are included in the sampled network. This leads us to generate eight sampled networks whose size gradually increases from 1,000 to 8,000 chains. For each sampled network, we compute $\max(AS_i)$. The procedure is then reproduced 100 times. Figure 7 reports $\max(AS_i)$ for each of the eight sampled networks included in each of the 100 simulations. Each black line corresponds to a set of eight sampled networks of increasing size. For any given sample size, the red line reports the mean value of $\max(AS_i)$ observed across all 100 sampled networks.

By construction, as the number of chains increases, the maximum absolute systemicness in sampled networks converges towards its actual value in the entire observed network (7.83%). In line with the intuition presented above, we also find that $\max(AS_i)$ tends to decrease when sample size increases. This finding is due to the fact that an incomplete network constructed from randomly sampling chains will tend to disproportionately feature highly systemic actors. Hence, our sampling method leads us to overestimate rather than underestimate actors' systemicness on the money market.

Figure 8 here

Second, we check whether this finding obtained on the observed network also holds when considering larger sample sizes and alternative network structures. We simulate 10 random networks and 10 scale-free networks featuring three times as many nodes and chains as the observed network (14,910 nodes and 26,664 chains). We then construct sampled subsections of these simulated networks as described above; first, by randomly selecting 2,000 chains; and then, by successively adding 2,000 randomly-selected chains to each sampled network until all 26,664 chains of the simulated network are included in the sample. We repeat this procedure five different times for each of the 10 simulated network in order to obtain 50 simulations. At every stage, we compute $\max(AS_i)$ for each sampled network.

Figure 8 reports the results. They reveal that, for both types of simulated networks, maximum systemicness tends to decrease as sample size increases. These results confirm that sampling biases lead us to overestimate systemicness in the true network and can therefore not affect our main conclusion that systemicness was relatively low on the sterling money market at the start of the twentieth century.

4.3. Group systemicness

We then investigate whether the sterling money market was resilient to shocks affecting specific groups of money market intermediaries. For that purpose, we identify four different groups of intermediaries in our network whose role has been described by contemporaries and financial historians alike:

1. *Discount houses*: these 20 institutions were comparable to modern money market funds and specialized in investing on the money market by purchasing large amounts of sterling bills of exchange (King, 1936; Accominotti et al., 2021).
2. *Anglo-foreign banks*: these 45 institutions were UK-based multinational commercial banks that intermediated credit through their many overseas branches (Jones, 1993);
3. *Merchant banks* (or *acceptance houses*): this group is composed of the top-10, globally-renowned investment banks (merchant banks) of the London City. These banks specialized in guaranteeing (accepting) bills of exchange on account of their domestic and overseas clients (Chapman, 1984).

4. *Clearing banks*: This group is composed of the 11 banks that dominated domestic commercial banking in the United Kingdom (Sykes, 1926).

Table 5 here

To analyse the significance of these four groups for agents' access to the sterling money market, we remove each group $G_x \in V$ from the network and compute their *absolute systemicness* AS_{G_x} and their *market share* MS_{G_x}:

The procedure is similar to that described in Algorithm 1, except that we now measure the joint absolute systemicness of all nodes that belong to a given group G_x rather than the systemicness of individual nodes.[18] The results of these computations are shown in Table 5. It is evident that discount houses (money market funds) were the overly dominant lenders on the money market with a combined market share of 65.65%. If all these intermediaries had failed at the same time, 42.1% of agents would have lost access to the sterling money market. While this would have represented significant damage for the financial network, this also suggests that there existed alternative routes that allowed accessing London's financial facilities without going through these institutions. Absolute systemicness was lower for other groups of intermediaries ranging from 5.7% for the UK clearing banks (domestic commercial banks) to 21.2% for the Anglo-foreign banks (UK-based multinational commercial banks). The relatively higher systemicness of the latter group of banks arises from their joint activity as guarantors and lenders of short-term funds for their overseas clients. Nevertheless, while the removal of each of these various groups would have caused significant disruptions to the money market, no group of intermediaries was sufficiently systemic for its removal to cause a complete collapse of the financial network and cut off all agents' access to that market.

[18] Note that a given group G_x's absolute systemicness differs from the sum of absolute systemicness values of all individual nodes that compose it. This is because all nodes of a given group are removed at the same time and these nodes often appear in the same chains.

4.4. Geographic systemicness

Borrowers on the London money market were located everywhere in the world and London financial intermediaries often specialized along geographic lines (Accominotti et al., 2021). Therefore, it is possible that certain geographical regions were strongly dependent on specific actors for their access to short-term sterling credit facilities. For example, if all borrowers from a certain region accessed the money market through the intermediation of one single London guarantor or lender, the failure of these intermediaries would have resulted in an entire region being cut off from the London money market.

Figure 9 here

We thus exploit our data on money market borrowers' geographical location to assess how dependent individual cities were on specific London intermediaries. Our dataset includes 617 cities. In Figure 9, we report the frequency distribution of these cities according to the number of borrowers they comprise. Money market borrowers were scattered across the world and many of them were located in relatively small cities. Hence, 53.65% of cities in the network featured only one borrower, while only 21.1% had five or more borrowers. Table 6 reports the list of all cities in the network classified according to the number of borrowers they featured.

Table 6 here

For each node i playing the role of guarantor or/and lender in the network, and for each city c in our database, we compute a *city market loss rate* $CMLr_{ci}$ corresponding to the share of borrowers of city c that lose market access when i is removed from the network. $CMLr_{ci}$ is formally defined in Algorithm 3.

Algorithm 3 here

We consider that a money market intermediary i is geographically systemic with respect to a given city c when $CMLr_{ci}$ is equal or higher than 50% or, in other words, when more than half of that city's borrowers lose market access as a result of the intermediary's failure. Out of the 1,535 guarantors and lenders in our dataset, only 63 were geographically systemic for at least one city. Of course, cities featuring one borrower only appear in one chain in the network and are by definition fully dependent on one guarantor and one lender for their market access. For those cities therefore, the lender's and guarantor's city market loss rates are both equal to 100% by construction.

Figure 10 here

In Figure 10, we focus on cities that comprise at least two borrowers. We represent relationships between all these cities and intermediaries in a matrix form. A dot on the graph indicates that a given intermediary is geographically systemic for a given city. The dot's size varies according to the number of borrowers present in that city while its color varies according to the intermediary's level of systemicness with regards to the city (measured through its city market loss rate). For example, looking at the interaction of the first column and bottom line in the graph, we see that Boston featured 23 different borrowers on the London money market and that 61% of them were dependent on one London intermediary (the discount house Union Discount Company) for their market access.

Several London intermediaries that specialized in intermediating credit for borrowers located in specific regions of the world were geographically systemic for specific cities in these regions. This is the case, for example, of the Canadian Bank of Commerce (a multinational bank that specialized in the financing of North American trade), on which borrowers in San Francisco, Pensacola, Toronto, Wilmington, Paris (Texas), Vancouver, and Navasota were strongly dependent. Similarly, C Murdoch & Co. (a merchant bank that specialized in guaranteeing bills for customers located in Africa) was a key intermediary for most borrowers in Casablanca, Mogador, Tangier, and Saffi. At the same time, even the largest discount houses or money market funds of the London City (Union Discount Company, National Discount Company, Alexanders & Co.) did not exhibit much geographical systemicness with regard to any city in the world. Overall, the results reveal that, except for a few of them, cities did not depend on one single intermediary for accessing the London money market.

4.5. City vulnerability

Last, we measure to what extent each city in the network was vulnerable to shocks on London intermediaries. A money market borrower was particularly vulnerable if its market access depended exclusively on one single guarantor or lender. For example, a borrower might have been involved in five different chains featuring five different lenders but only one guarantor. In that case, the borrower was strictly dependent on one guarantor for its market access but did not depend on any specific lender. We consider that a given borrower is *vulnerable* when its market access depends on one single guarantor or lender. We also distinguish between *guarantor-vulnerable* borrowers (i.e., borrowers that depend on one single guarantor) and *lender-vulnerable* borrowers (i.e., borrowers that depend on one single lender).

For each city c, we compute both a *guarantor-vulnerability rate* VUL_{Gc} (defined as the share of borrowers of that city that depend on one single guarantor) and a *lender-vulnerability rate* VUL_{Lc} (defined as the share of borrowers of the city that depend on one single guarantor). The formal definitions of VUL_{Gc} and VUL_{Lc} are provided in Algorithm 4.[19]

Algorithm 4 here

Figure 11, Panel A, presents a scatter plot of cities' VUL_{Gc} against their overall number of borrowers. Then, 40.0% of the cities appearing in at least two chains exhibit a guarantor-vulnerability rate of 100%, indicating that each of their borrowers is dependent on one single guarantor. All of these highly guarantor-

[19] Cities that appear in one single bill of the network have, by construction, a vulnerability score of 100%. Hence, we restrict our sample to the 360 cities that appear in at least two bills.

vulnerable locations were however small cities comprising 10 borrowers or less. At the same time, not all small cities exhibited a high VUL_{Gc}. Out of the 296 cities that featured 10 borrowers or less, 16.9% had no guarantor-vulnerable borrower and 29.7% had less than half of their borrowers that were guarantor-vulnerable. At the other end of the spectrum, no single city with more than 10 borrowers exhibited a guarantor-vulnerability rate of 100%.

Figure 11 here

Figure 11, Panel B, scatters cities' VUL_{Lc} against their overall number of borrowers. On average, cities appear to have been less exposed to the removal of lenders than guarantors. The share of cities with a vulnerability rate of 100% is lower for lenders (31.9%) than for guarantors (40.0%).[20] In addition, while 16.7% of cities in the network feature no lender-vulnerable borrowers, only 13.9% of cities have no guarantor-vulnerable borrower.

Overall, these findings indicate that lenders were on average more substitutable money market intermediaries than guarantors. Borrowers obtained funds from a relatively diverse pool of lenders but had their debts guaranteed by a more limited number of guarantors. At the same time, the 20 biggest lenders on the money market had a significantly higher market share (85.35%) than the 20 biggest guarantors (37.52%). Therefore, despite the greater market concentration in lending than in guaranteeing, intermediaries playing the role of guarantors were less substitutable. This apparent paradox can be explained by the specific nature of these two types of activities, which were performed by different types of money market intermediaries (Accominotti et al., 2021). One implication of this market structure is that the sterling money market did not feature very large and systemic hubs, and was less prone to the *robust-yet-fragile* property characteristic of most present-day interbank networks.

[20] It is worth noting however that two out of the 115 cities (Port Said and Amsterdam) that exhibit a vulnerability rate of 100% with respect to lenders are middle-sized cities that featured 15 and 20 borrowers, respectively.

5. Conclusions

We rely on a new dataset assembled from archival records in order to reconstruct the network of financial interlinkages in the dominant global money market of the first globalization era. This dataset covers both "bank-bank" (lender-guarantor) and "bank-firm" (guarantor-borrower) relationships. We represent the network of borrower-guarantor-lender intermediation chains as a hyperstructure and assess financial network resilience through an original methodology that allows preserving the unity of these higher-order structures. We apply simple shock simulation techniques and measure the effect of removing individual nodes (or intermediaries) on the overall network. This allows us to measure to what extent money market intermediaries were substitutable and to what extent borrowers across the world were dependent on a few London agents for their access to the dominant global money market.

In modern interbank networks, shock simulations involving the removal of central nodes generally result in a complete breakdown of network connectivity. This is because present-day networks are generally characterised by the presence of a few systemic and non-substitutable actors. Our findings however indicate that the sterling money market of the first globalization era did not feature any highly-systemic intermediaries, whose failure could have caused major damage to the network. These findings indicate that a global financial network with a low level of actors' systemicness can and did actually exist even at a time of high international financial integration.

Our paper makes a methodological contribution. To the best of our knowledge, we are the first to apply the hyperstructure approach to the study of financial networks. The methodology we develop here could be applied to study the resilience of any directed network in which certain nodes are non-substitutable and can potentially cause severe damage to connectivity. This is the case, for example, of global supply chains or transportation networks (Lucena-Piquero et al., 2022).

Our results also have implications for financial regulators. The low systemicness of intermediaries on the sterling money market at the beginning of the twentieth century arose from the specific characteristics of the financial instruments (bills of exchange) used for money market transactions. These instruments created incentives for money market agents to produce information on borrowers and discouraged the emergence of too large intermediaries (Accominotti et al., 2021). Nineteenth-century regulators were adamant about the superiority of the bill of exchange from a supervisory viewpoint (Ugolini, 2017). This suggests that supervisors aiming to improve the robustness of financial networks should pay close attention to the microstructure of financial markets and encourage the use of instruments whose design provides disincentives to concentration.

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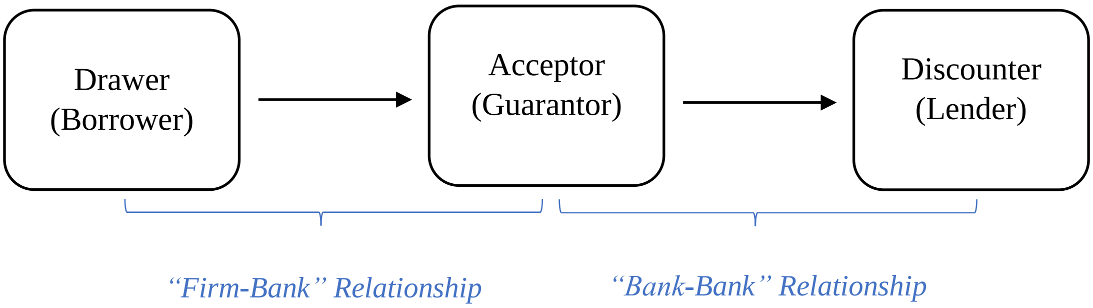
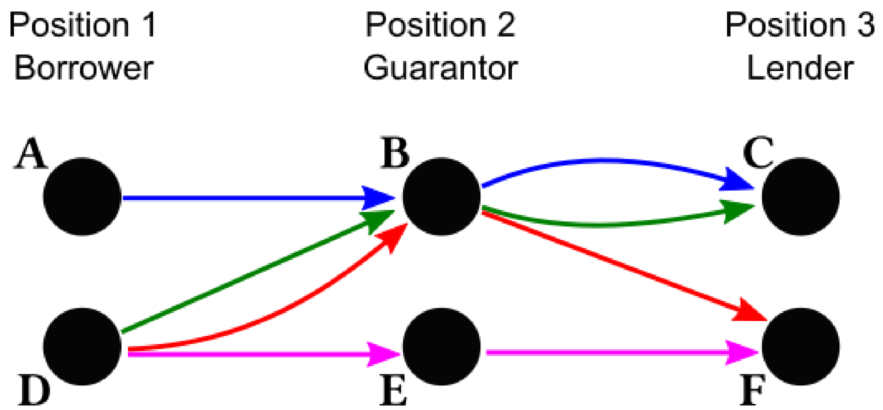
Figure 1. Links encompassed in a bill of exchange



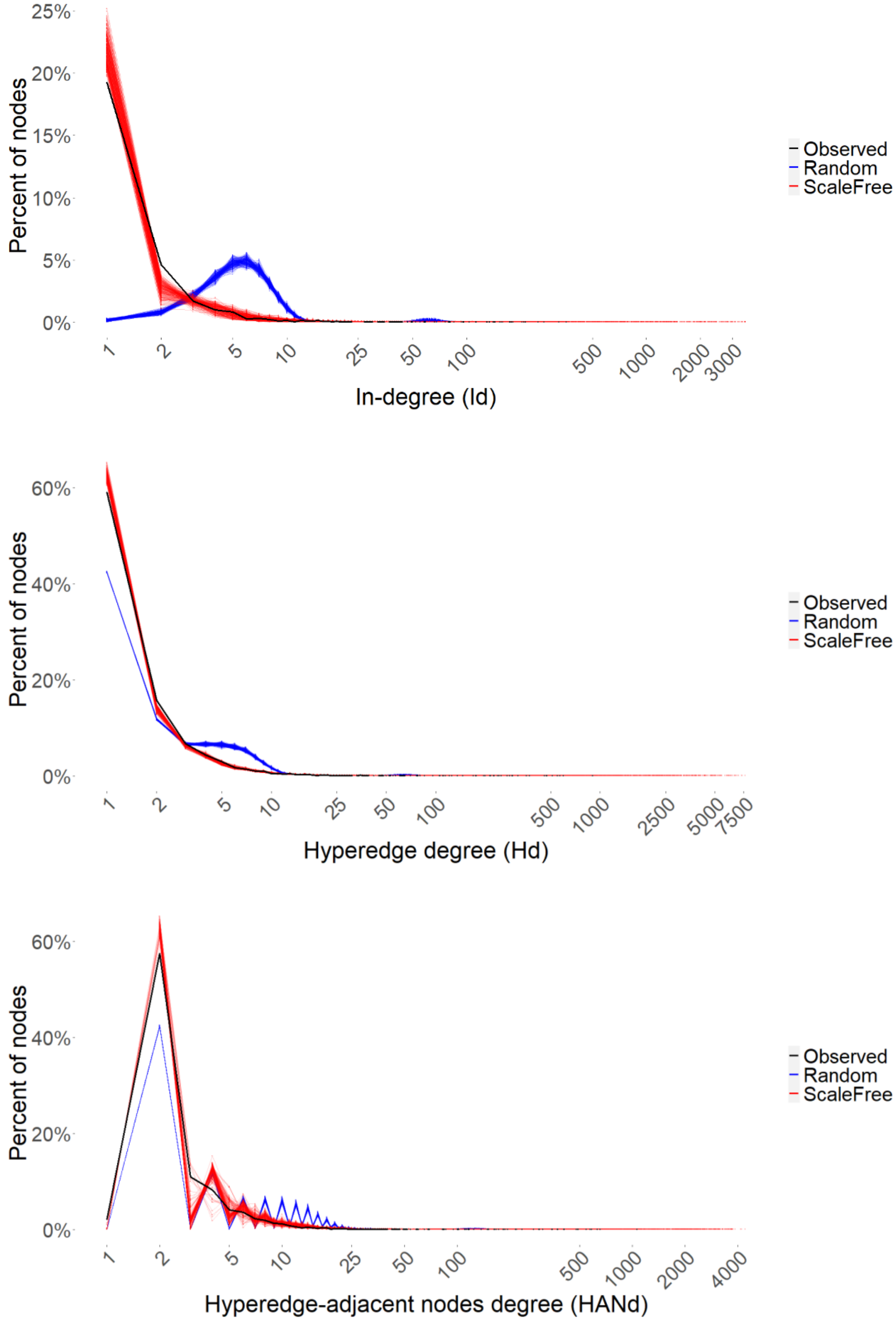
Notes: This figure presents a schematic representation of the relationships between actors involved in the origination and distribution of a bill of exchange. See Accominotti et al. (2021) for a detailed description of the functioning of bills of exchange.

Figure 2. Representation of chains



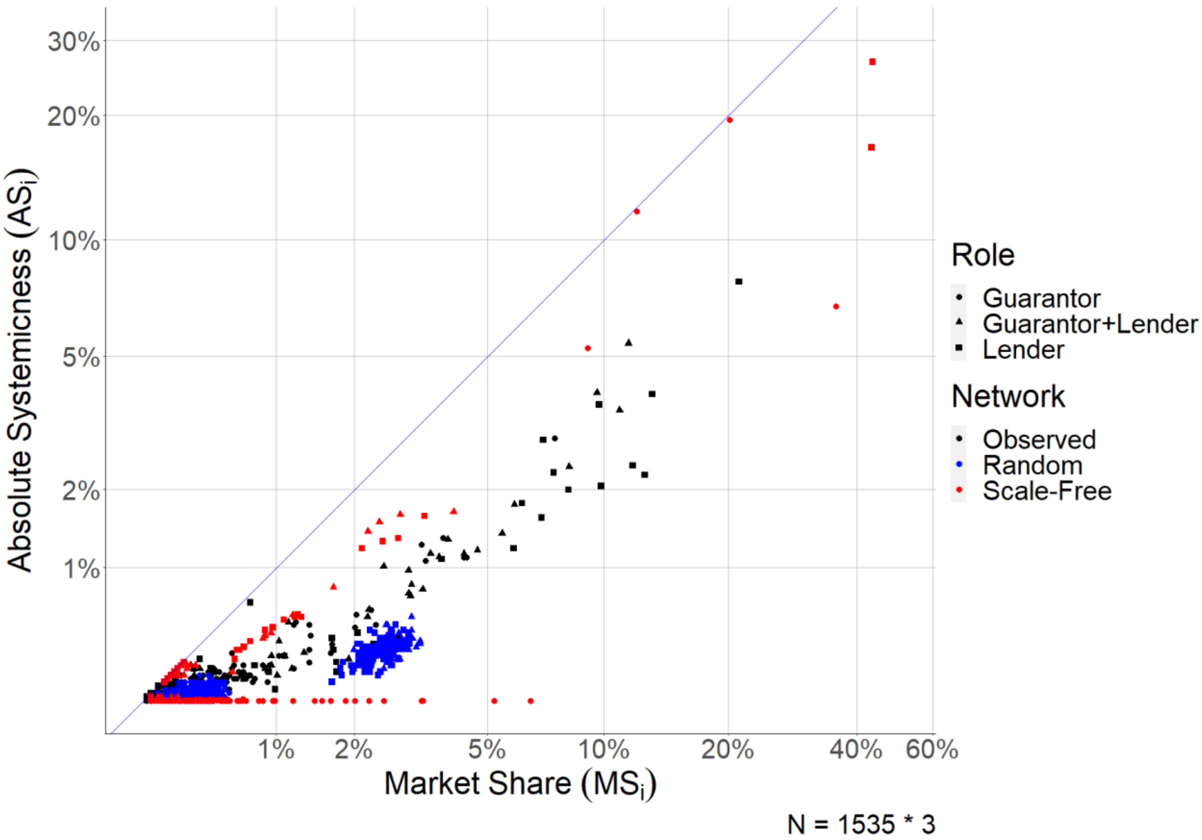
Notes: This figure presents a hypothetical example of a higher-order network involving four chains and six nodes. The four chains are (A,B,C), (D,B,C), (D,B,F) and (D,E,F). Each combination of two same-coloured arrows constitutes a hyperedge that associates the three nodes and their links in a given chain.

Figure 3. Node degree distribution: observed versus *null* model networks



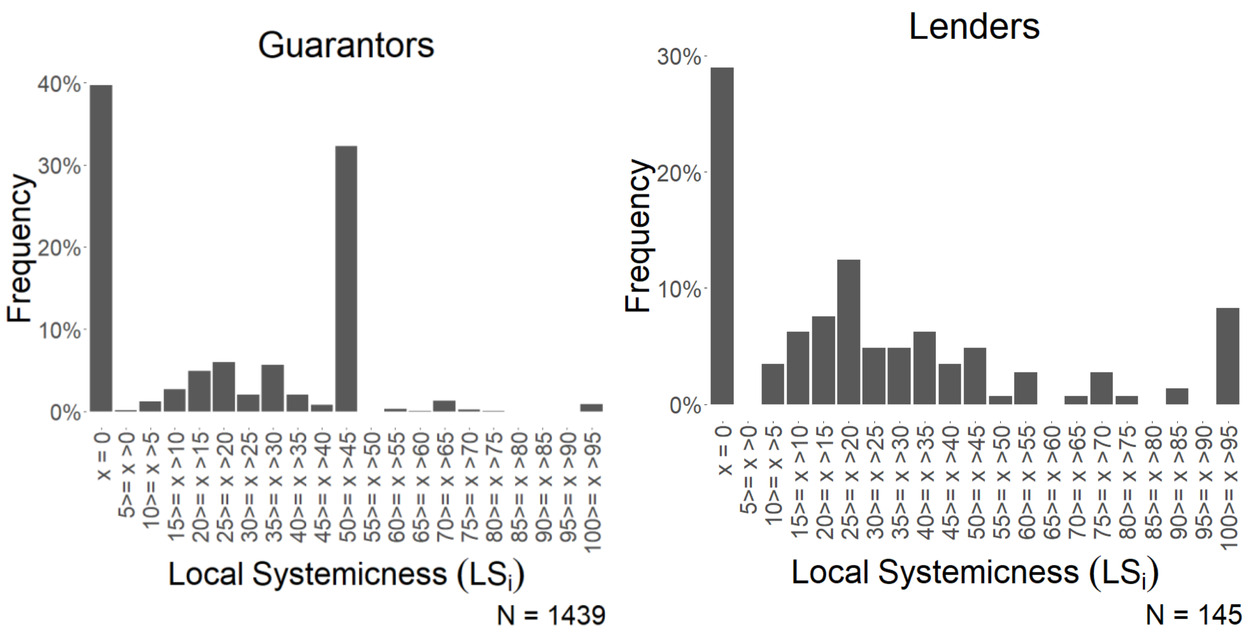
Notes: For each of the three network degree centrality metrics, the figure shows the frequency distribution of nodes according to their degree in the observed network (black line), in 250 simulated random networks (blue lines), and in 250 simulated scale-free networks (red lines). Panel A reports the frequency distribution of nodes according to their *in-degree* (Id_i). Panel B reports the frequency distribution of nodes according to their *hyperedge degree* (Hd_i). Panel C reports the frequency distribution of nodes according to their *hyperedge-adjacent nodes degree* ($HANd_i$). The x-axis is in logarithmic scale. Nodes that only played the role of borrower are excluded from panel A as, by construction, $Id_i = 0$ for those nodes. See text.

Figure 4. Absolute systemicness



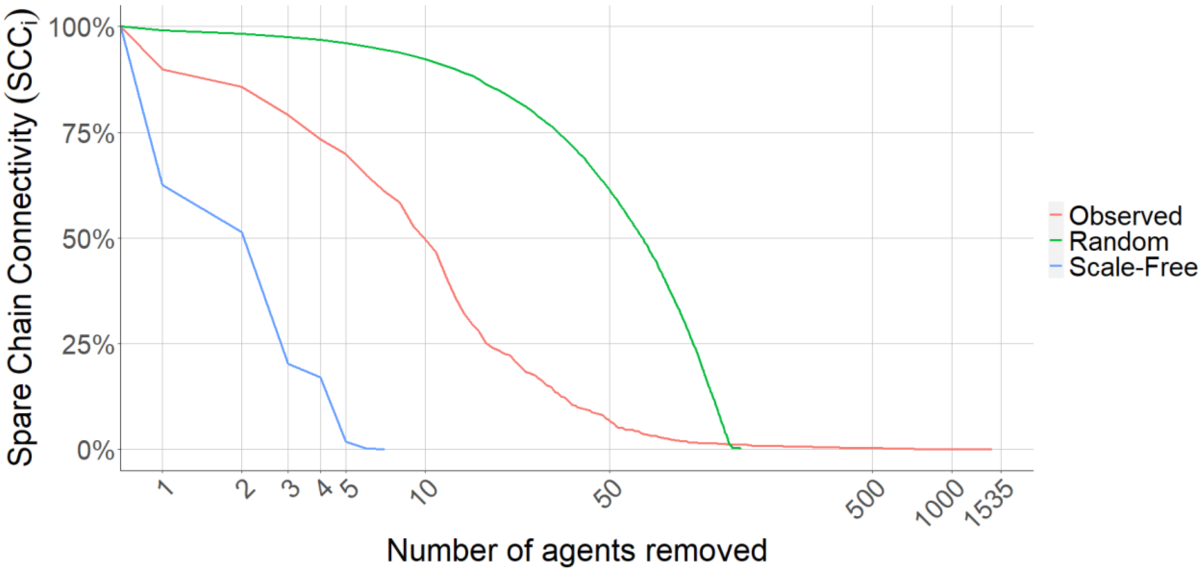
Notes: The figure reports the *absolute systemicness* (AS_i) and *market share* (MS_i) of each intermediary (guarantor or lender) in the observed network as well as in one simulated random network and one simulated scale-free network. On the y-axis, a node i's *absolute systemicness* corresponds to the percentage of all nodes in the network that remain isolated when i is removed. On the x-axis, a node i's *market share* corresponds to the percentage of nodes in the network which are hyperedge-adjacent to i). See text for a more detailed definition of these variables. Actors of the observed, random and scale-free networks are represented in black, blue, and red, respectively. In each network, nodes that only played the role of guarantor are represented by a dot, nodes that only played the role of lender are represented by a square, and nodes that played the role of both guarantor and lender are represented by a triangle. Both axes are in logarithmic scale. See text.

Figure 5. Local systemicness: guarantors and lenders



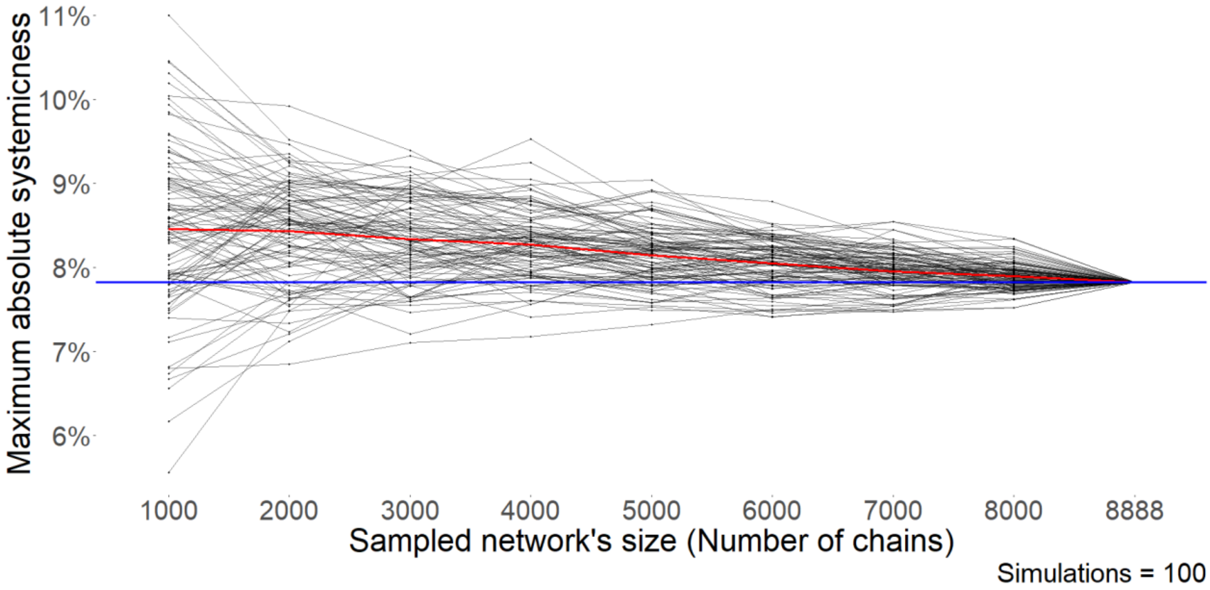
Notes: The figure reports the frequency distribution of guarantors (left panel) and lenders (right panel) according to their *local systemicness* (LS_i). Values on the y-axis correspond to the percentage of guarantors/lenders whose LS_i falls within any given value range reported on the x-axis. See text.

Figure 6. Spare Chain Connectivity



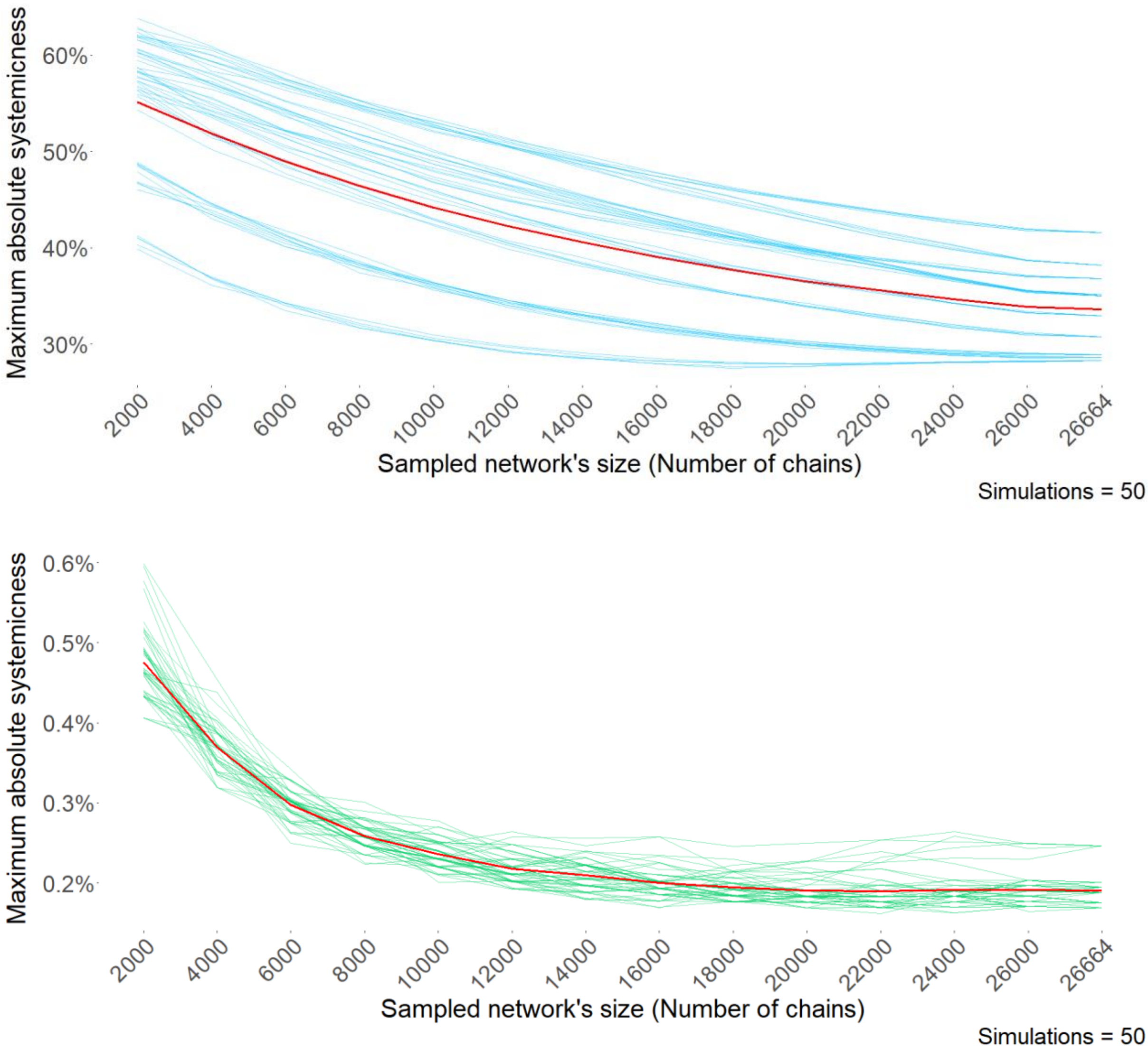
Notes: For each of the observed network, simulated random network and simulated scale-free network, the y-axis reports the percentage of original chains that are preserved after sequentially removing a certain number of nodes. Nodes are sequentially removed in the order of their absolute systemicness (AS_i). The x-axis is in logarithmic scale. See text.

Figure 7. Sampling effects and systemicness in the observed network



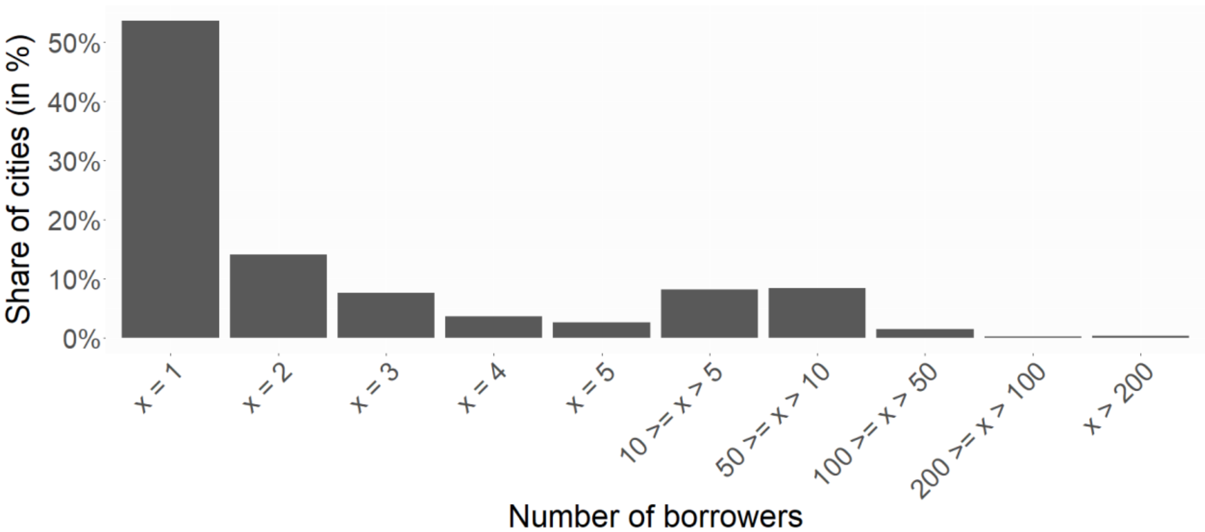
Notes: The figure reports the outcome of simulations performed to assess the effect of sampling biases on maximum absolute systemicness in the observed network. Each of the 100 black lines reports the *maximum absolute systemicness* ($\max(AS_i)$) recorded in eight randomly-sampled portions of the observed network. Sampled networks are increasing in size from 1,000 to 8,000 chains. The observed network contains 8,888 chains. The number of chains included in each sampled portion of the observed network is reported on the x-axis and $\max(AS_i)$ is reported on the y-axis. For any given sample size, the red line corresponds to the mean of $\max(AS_i)$ across all 100 sampled networks. The horizontal blue line crosses the y-axis at 7.83% (i.e., the maximum value of AS_i in the observed network). See text.

Figure 8. Sampling effects and systemicness in random and scale-free networks



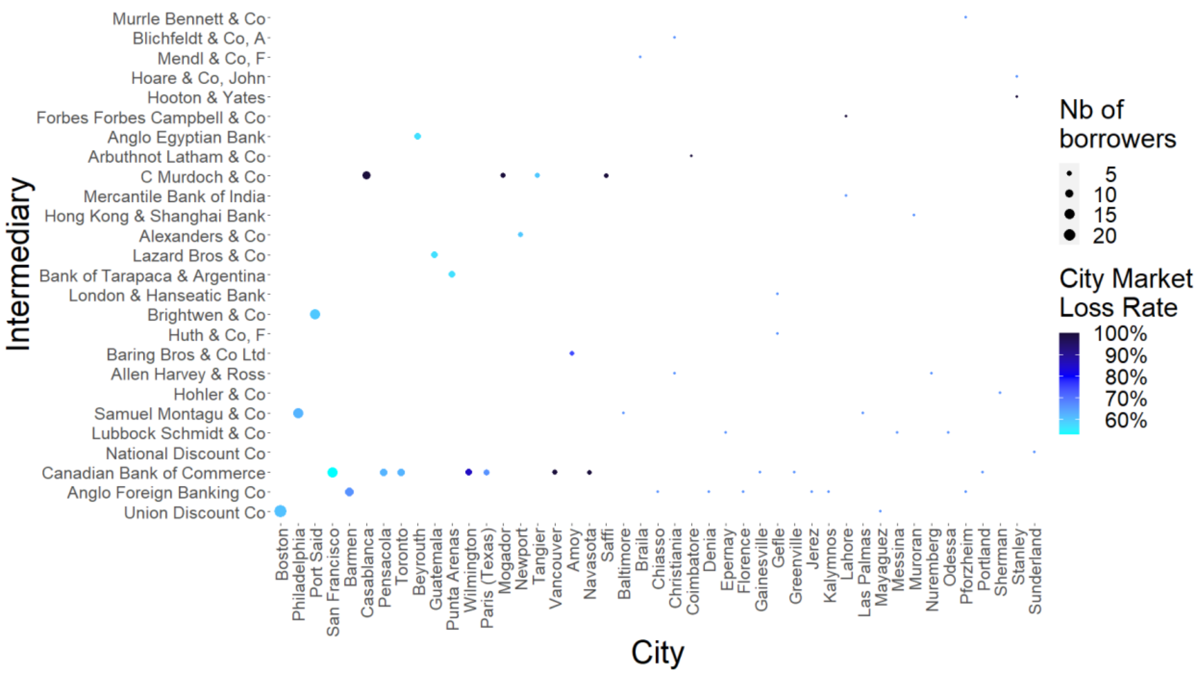
Notes: The figure reports the outcome of simulations performed to assess the effect of sampling biases on maximum absolute systemicness in random and scale-free networks. Each of the 50 blue (green) lines reports the *maximum absolute systemicness* ($\max(AS_i)$) recorded in fourteen randomly-sampled portions of ten simulated random (scale-free) networks. Sampled networks are increasing in size from 2,000 to 26,664 chains. Each of the ten simulated networks contains 26,664 chains. The x-axis reports the number of chains included in each sample of the simulated random (scale-free) network. The y-axis reports $\max(AS_i)$ for each sample. For any given sample size, the red line corresponds to the mean of $\max(AS_i)$ across all 50 sampled networks. See text.

Figure 9. Frequency distribution of cities according to their number of borrowers



Notes: The figure reports the frequency distribution of cities according to the number of borrowers they feature. Values on the y-axis correspond to the percentage of cities that comprise a number of borrowers falling within any given value range reported on the x-axis. See text.

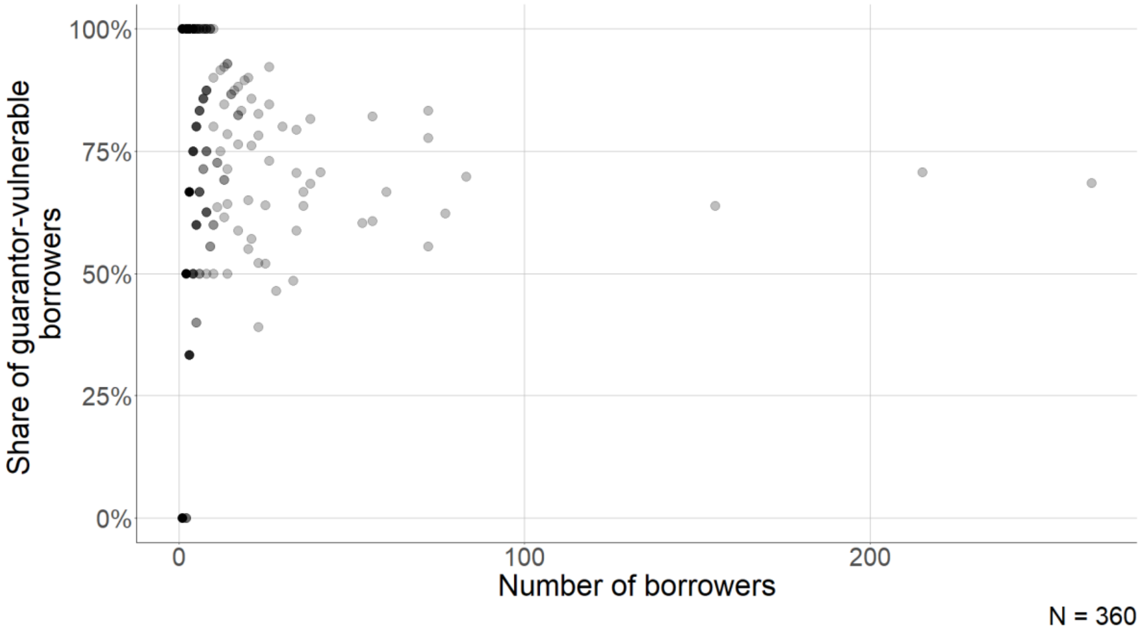
Figure 10. Geographically systemic intermediaries



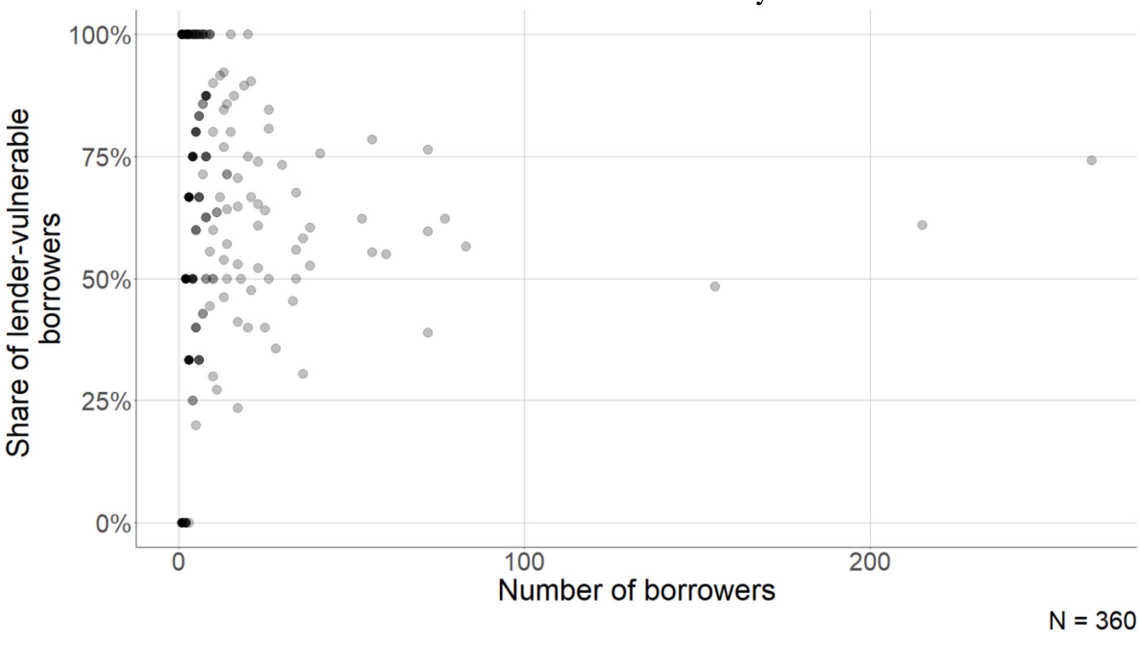
Notes: The figure represents all intermediaries (guarantors and lenders) that were geographically systemic with respect to cities that appear on the x-axis. All cities featuring at least two borrowers are included. An intermediary is considered geographically systemic for a given city if more than 50% of borrowers of that city lose market access as a consequence of its removal. For every city, geographically systemic intermediaries are represented by a blue dot. The dot's size varies according to the number of borrowers located in the city and its darkness varies according to the intermediary's *city market loss rate* ($CMLr_c$) with regards to that city. On the x-axis, cities are ranked (from left to right) according to their overall number of borrowers. On the y-axis, intermediaries are ranked (from bottom to top) according to their *absolute systemicness* (AS_i). See text.

Figure 11. City vulnerability

Panel A. Guarantor-vulnerability



Panel B. Lender-vulnerability



Notes: For each city with at least two bills in the network, the figure reports its overall number of borrowers (x-axis) and the percentage of these borrowers that are *guarantor-vulnerable* (Panel A) and *lender-vulnerable* (Panel B) (y-axis). A borrower is considered guarantor- (lender-)vulnerable if it is dependent on one single guarantor (lender) for its market access. Cities that appeared in one single chain in the network are removed from the analysis as, by construction, 100% of their borrowers were vulnerable. Each dot on the figure corresponds to one city. Several cities exhibit the exact same number of overall and vulnerable borrowers, in which case their dots are superimposed. Superimposed dots appear darker on the figure. See text.

Algorithm 1: Absolute systemicness, market share, and local systemicness

Input:

Data as an edgelist E where each row is a chain (a bill in our case) and each column is a role (three columns in our case). The set of chains (rows) in E is C, each row is unique in E (no two chains are alike), and V is the set of agents in E.

Procedure:

1. Identify all agents i in guarantor and/or lender role (subset $V_{GL} \in V$): $\{i\} \in V_{GL} \; \forall \{i\} \in V : Id_i > 0$
2. FOR i in V_{GL}, subset from E all rows where the agent i has the guarantor and/or lender role. The result is the edgelist E_i
3. Obtain the edgelist R_i via the subtraction of the edgelist E_i from E, so $R_i = E \setminus E_i$
4. Obtain the subset V_{pi} of agents included in E_i excluding i: $V_{pi} = \{j \in V : j \in E_i\} \setminus \{i\}$
5. Obtain the subset V_{si} of agents who are included in V_{pi} but not in R_i (i.e., the agents who depend on i for market access): $V_{si} = V_{pi} \setminus \{j \in V : j \in R_i\}$
6. Compute the *absolute systemicness* of an agent i (AS_i) as the proportion of agents of V_{si} in V less one (the agent i): $AS_i = (|V_{si}|/(|V| - 1))$
7. Compute the *market share* of an agent i (MS_i) as the proportion of agents of V_{pi} in V less one (the agent i): $MS_i = (|V_{pi}|/(|V| - 1))$
8. Compute the *local systemicness* of an agent i (LS_i) as the proportion of agents of V_{si} in V_{pi}: $LS_i = (AS_i/MS_i) = (|V_{si}|/|V_{pi}|)$

Algorithm 2: Spare chain connectivity

Input:
Data as an edgelist E where each row is a chain (a bill in our case) and each column is a role (three columns in our case). The set of chains (rows) in E is C, each row is unique in E (no two chains are alike), and V is the set of agents in E. The absolute systemicness AS for all guarantors and lenders V_{GL}
Procedure:
1. Order (permute) V_{GL} elements by decreasing absolute systemicness. The result is the sequence of agents VAS. 2. FOR i = 1 to $\|VAS\|$ 3. IF i = 1 : $E_R == E$; $C_R == C$; $V_R == V$ 4. Obtain from E_R all rows where i has the guarantor and/or lender roles. The result is the edgelist E_i. 5. Redefine E_R as E_R without E_i : $E_R = E_R \; / \; E_i$ 6. Obtain the set of chains C_{Ri} from the edgelist E_R. 7. Compute the *spare chain connectivity* SCC as the proportion of chains remaining in the network after removing the agent i and all its predecessors in the VAS sequence. So, $SCC_i = \|C_{Ri}\| \; / \; \|C\|$ 8. IF $E_R = \{\}$ ENDFOR

Algorithm 3: City market loss rate

Input:

Data as an edgelist E where each row is a chain (a bill in our case) and each column is a role (three columns in our case). The set of chains (rows) in E is C, each row is unique in E (no two chains are alike), and V is the set of agents in E.
Data frame of borrowers by city. The set of borrowers is DR and the set of cities is CT.

Procedure:

1. FOR c in CT, subset from E all rows (chains) whose agents playing the role of borrowers are located in city c. The result is the subset of agents and chains E_c, where C_c is the subset of chains in E_c and DR_c is the subset of agents in borrower role in E_c
2. IF $|C_c| > 1$:
3. Identify all actors i with guarantor and/or lender role in E_c. The result is the subset V_{GL_c}
4. FOR i in V_{GL_c}, subset from E_c all rows (chains) where i has the guarantor and/or lender role. The result is the subset of chains and agents E_{ci}
5. Obtain the subset of chains and agents R_{ci} which are not included in E_{ci}: $R_{ci} = E_c \setminus E_{ci}$
6. Obtain the subset DR_{ci} of agents (borrowers) of E_{ci} who are not included in R_{ci} (i.e., the agents who depend on i for market access): $DR_{ci} = E_{ci} \setminus R_{ci}$
7. Compute the *city market loss rate* of a city c for an agent i ($CMLr_{ci}$) as the proportion of the borrowers in city c (i.e., of DR_c) who depend on agent i for market access: $CMLr_{ci} = (|DR_{ci}|/|DR_c|)$

Algorithm 4: City vulnerability

Input:

Same as Algorithm 3.

Procedure:

1. FOR c in CT, subset from E all rows (chains) whose agents playing the role of borrowers are located in city c. The result is the edgelist E_c, where C_c is the subset of chains in E_c and DR_c is the subset of agents in borrower role in E_c
2. IF $|C_c| > 1$:
3. FOR i in DR_c identify both subsets of agents in guarantor role V_{G_c} and in lender role V_{L_c}. If $|V_{G_c}| = 1$, the borrower i is *guarantor-vulnerable*. If $|V_{G_L}| = 1$, the borrower i is *lender-vulnerable*.
4. Define $DR_{Gc} \in DR_c$ as the set of *guarantor-vulnerable* borrowers in city c. Define $DR_{Lc} \in DR_c$ as the set of *lender-vulnerable* borrowers in city c.
5. Compute city c's *guarantor-vulnerability* VUL_{Gc} as the proportion of the borrowers in city c who are guarantor-vulnerable: $VUL_{Gc} = (|DR_{Gc}|/|DR_c|)$. Compute city c's *lender-vulnerability* VUL_{Lc} as the part of the borrowers in city c who are lender-vulnerable: $VUL_{Lc} = (|DR_{Lc}|/|DR_c|)$

Table 1: Profiles of agents on the sterling money market

Profile	Number	% of all agents	% of London-based agents
Pure Borrower (outside London)	3,290	66.20	-
Pure Borrower (in London)	145	2.92	8.63
Pure Guarantor	1,326	26.68	78.93
Hybrid (Borrower+Guarantor)	64	1.29	3.81
Pure Lender	61	1.23	3.63
Hybrid (Borrower+Lender)	35	0.70	2.08
Hybrid (Guarantor+Lender)	29	0.58	1.73
Hybrid (Borrower+Guarantor+Lender)	20	0.40	1.19
Total	4,970	100.00	100.00

Notes: This table presents the number of agents of different profiles on the sterling money market as well as their share in the total population of agents and in the population of London-based agents. "Pure" refers to nodes playing only one role (borrower or guarantor or lender) in the various bills in which they are involved. "Hybrid" refers to nodes that play different roles in the various bills on which they appear. Note that any agent playing the role of guarantor or lender had to be located in London. See text.

Table 2: Degree centrality measures in a hyperstructure: an example

Node (i)	**In-degree** (Id_i)	**Hyperedge degree** (Hd_i)	**Hyperedge-adjacent nodes degree** ($HANd_i$)
A	0	1	2
B	2	3	4
C	1	2	3
D	0	2	3
E	1	1	2
F	2	2	3

Notes: This table illustrates three network degree centrality metrics for nodes in a hyperstructure. For each node A, B, C, D, E, F, in the hypothetical network represented in Figure 2, the table reports their *in-degree*, *hyperedge degree* and *hyperedge-adjacent degree*. See text for the three degree definitions.

Table 3. Maximum node degree value in observed and simulated networks

Measure	Network type	Nb of networks	Min	Max	Mean	Median
Maximum In-degree ($\max(Id_i)$)	Observed	1	357	357	357	357
	Random	250	77	97	85	84
	Scale-Free	250	895	3555	2192	2020
Maximum Hyperedge degree ($\max(Hd_i)$)	Observed	1	900	900	900	900
	Random	250	89	127	108	108
	Scale-Free	250	896	7666	3434	3100
Maximum Hyperedge-Adjacent Nodes degree ($\max(HANd_i)$)	Observed	1	1055	1055	1055	1055
	Random	250	171	239	204	203
	Scale-Free	250	1218	4417	2684	2566

Notes: This table presents descriptive statistics (minimum, maximum, mean and median) on the maximum degree values observed in a. the observed network, b. the 250 simulated random networks, and c. the 250 simulated scale-free networks. See text for the definition of the three degree values and for details on the simulations.

Table 4. Maximum absolute systemicness and maximum market share in observed and simulated networks

Measure	Network type	Nb of networks	Min	Max	Mean	Median
Maximum Absolute Systemicness ($\max(AS_i)$)	Observed	1	7.828	7.828	7.828	7.828
	Random	250	0.442	0.684	0.530	0.523
	Scale-Free	250	9.297	68.554	31.967	29.070
Maximum Market Share ($\max(MS_i)$)	Observed	1	21.231	21.231	21.231	21.231
	Random	250	3.099	4.004	3.399	3.380
	Scale-Free	250	16.312	76.533	53.815	53.547

Notes: This table presents descriptive statistics (minimum, maximum, mean and median) on the maximum values of absolute systemicness and market share observed in a. the observed network, b. the 250 simulated random networks, and c. the 250 simulated scale-free networks. See text for the definition of the two variables and for details on the simulations.

Table 5. Group systemicness

Group of intermediaries	Number of impacted nodes ($\lvert V_{sG_x} \rvert$)	Absolute systemicness (AS_{G_x})	Market share (MS_{G_x})
Discount houses (N=20)	2094	42.1%	65.7%
Anglo-Foreign Banks (N=45)	1053	21.2%	40.6%
Top-10 Merchant Banks (N=10)	569	11.5%	22.3%
Clearing Banks (N=11)	281	5.7%	11.6%

Notes: For each of the four historical groups of intermediaries (discount houses, Anglo-foreign banks, top-10 merchant banks, and clearing banks), the table reports the number of nodes that remain isolated when the entire group is removed from the network ($\lvert V_{sG_x} \rvert$), the group's *absolute systemicness* (AS_{G_x}), as well as the group's *market share* (MS_{G_x}). See text and Algorithm 1 for the formal definition of each indicator.

Table 6. Demography of cities

Number of borrowers per city	Number of cities in that category	City names
200+	2	London; New York.
101-200	1	Calcutta.
51-100	9	Alexandria; Bombay; Buenos Aires; Colombo; Hamburg; Manchester; Memphis; New Orleans; Yokohama.
11-50	52	Amsterdam; Antwerp; Bahia; Barmen; Batavia; Belfast; Berlin; Bordeaux; Boston; Bradford; Bremen; Cairo; Chicago; Constantinople; Copenhagen; Dallas; Galveston; Glasgow; Havana; Hong Kong; Houston; Iquique; Karachi; Kobe; Lima; Liverpool; Madras; Malaga; Manila; Melbourne; Montevideo; Montreal; Norfolk; Para; Paris; Pernambuco; Philadelphia; Port Said; Rangoon; Riga; Rio de Janeiro; San Francisco; Santos; Sao Paulo; Savannah; Shanghai; Singapore; Smyrna; St Petersburg; Stockholm; Sydney; Valparaiso.
6-10	50	Antofagasta; Arequipa; Augusta; Baghdad; Barbados; Beyrouth; Bilbao; Brussels; Bucharest; Casablanca; Dundee; Foochow; Fort Worth; Frankfurt; Genoa; Goteborg; Guatemala; Guayaquil; Hankow; La Paz; Leeds; Leipzig; Lisbon; Manaus; Marseille; Montgomery; Moscow; Oporto; Oruro; Paris (Texas); Patras; Penang; Pensacola; Port Elizabeth; Port of Spain; Punta Arenas; Rosario; Rotterdam; Salonica; San Jose; Santiago; Shimonoseki; St Louis; Surabaya; Tientsin; Toronto; Valencia; Waco; Wilmington; Zurich.
2-5	172	Adelaide; Aden; Algiers; Alicante; Almeria; Amoy; Amritsar; Athens; Atlanta; Auckland; Baltimore; Bangkok; Barcelona; Bari; Basle; Bassora; Birmingham (Alabama); Bogota; Braila; Brisbane; Brooklyn; Budapest; Campinas; Canton; Carrara; Cartagena; Castries; Cavalla; Ceara; Cedar Rapids; Ceylon; Charleroi; Charlotte; Chiasso; Christchurch; Christiania; Cienfuegos; Cochabamba; Coimbatore; Cologne; Como; Concepcion; Corfu; Corsicana; Crefeld; Curacao; Daitotei; Danzig; Demerara; Denia; Dunedin; Dusseldorf; Epernay; Fazilka; Florence; Fremantle; Gainesville; Galatz; Gefle; Greenville; Grenada; Halifax; Hamilton; Helena (Arkansas); Herisau; Hiogo; Invercargill; Iquitos; Jerez; Johannesburg; Jumet; Kalymnos; Kansas City; Keighley; Kristiansand; Labuan; Ladysmith; Laguna; Lahore; Langerfeld; Las Palmas; Le Havre; Leghorn; Leicester; Little Rock; Lodz; Lyon; Macassar; Macon; Malmoe; Managua; Mangalore; Maracaibo; Maranhao; Mauritius; Mayaguez; Mazagan; Medellin; Messina; Mexico; Milan; Minneapolis; Mobile; Mogador; Mosgiel; Muroran; Nagasaki; Naples; Navasota; Neckarau; Newcastle; Newport; Nuremberg; Odessa; Oklahoma City; Orizaba; Palermo; Panama; Parahyba; Paris (Arkansas); Passaic; Perth; Pforzheim; Ponce; Portland; Porto Alegre; Potosi; Prague; Puerto Gallegos; Quebec; Rio Grande; Rustchuk; Saffi; San Antonio; San Juan; San Salvador; Sandakan; Seattle; Sevilla; Sherman; Sorata; St Etienne; St Gall; St Vincent; Stanley; Sunderland; Syra; Tacna; Tangier; Teheran; Temple; Tenerife; The Hague; Townsville; Trieste; Tripoli; Troy; Tupiza; Turin; Vancouver; Venice; Veracruz; Verviers; Vicksburg; Victoria; Vienna; Vostizza; Warsaw; Wellington; Yazoo City; Zante; Zanzibar.
1	331	Aarau; Abilene; Abo (Turku); Ada (Oklahoma); Aguadilla; Akyab; Albany (Australia); Albany (Georgia); Americus; Amotfors; Andros; Ansbach; Antigua; Ardmore (Oklahoma); Arecibo; Arica; Ashgabat; Asuncion; Athens (Georgia); Aymeries; Bahama; Bamberg; Barnaul; Barrow in Furness; Barry; Bassein; Bayonne; Bergen; Bermondsey; Bielefeld; Binche; Birmingham; Blackburn; Bocholt;

Bochum; Bolivar; Bonham; Botosani; Bradford (New Zealand); Brenham; Brighouse; Broe; Brooketon; Broome; Brownwood; Brunswick; Burslem; Cadiz; Cairns; Calicut; Canaveral; Candia; Cape Town; Caracas; Cassel; Castlebar; Catacaos; Catania; Cathcart; Cawnpore; Cephalonia; Cernobbio; Charleston; Charlottetown; Chemainus; Chemnitz; Chickasha (Oklahoma); Church (Lancashire); Cincinnati; Cochin; Colonne; Colquechaca; Columbus (Georgia); Comber; Coquimbo; Cordele; Corocoro; Corumba; Costa Rica; Cuiaba; Cuthbert; Danville; Darwin; Dawson; Deerlijk; Denderleeuw; Denton; Derby; Dewsbury; Dison; Dixon; Dordrecht; Dothan; Drogheda; Dublin (Georgia); Dumbarton; Durban; Dyersburg; Emelghem; Enkhuizen; Espinho; Falkirk; Farmersville; Faro; Fortin; Frangsund; Fray Bentos; Frederiksberg; Fredneks; Fredrikstadt; Funchal; Gais; Galle; Gamleby; Gandia; Gibraltar; Gisborne; Goor; Gourdon; Govan; Granada (Nicaragua); Greenock; Greenwood; Grenada (Mississippi); Grimsby; Guerville; Guiria; Halberstadt; Hanmore; Harlingen; Heilbronn; Helsingborg; Henderson; Herberton; Hodeidah; Holstebro; Holzheim; Hoogezand; Hoorn; Howrah; Huddersfield; Humacao; Indianapolis; Jacksonville; Jaffna; Jaragua; Jersey; Jesselton; Johanngeorgenstadt; Jonkoping; Kalmar; Kazan; Keelung; Kerassunde; Kidderminster; Killik Aike; Kimberley; Kingston; Kirkcaldy; Klingenthal; Koenigsberg; Kuching; La Coruna; La Plata; La Salada; Langesund; Larnaca; Launceston; Lawrencetown; Leigh on Sea; Lerwick; Limon; Llagostera; Lodelinsart; Lulea; Lurgan; Maarssen; Maceio; Madeira; Madrid; Maffersdorf; Malta; Mantua; Marin; Marshalltown; Massena; Masterton; Matanzas; Medan; Merida; Middlesbrough; Mirzapur; Mistley; Moji; Moltann; Monro; Mossel Bay; Mulheim; Munich; Muscat; Napier; Narva; Natal; Nepal; Nessonvaux; Neustadt; Newbury; Newton; Norrkoping; Nuwara Eliya; Ollioules; Ootacamund; Opobo; Orlando; Otaru; Ottignies; Ottumwa; Oude Pekela; Padang; Pahepe; Palafrugell; Partick; Paysandu; Peking; Pepinster; Petit-Goave; Piacenza; Pictou; Pine Bluff; Pireus; Pisagua; Plano; Port Antonio; Puerto Cabello; Pyrgos; Quilon; Ravilloles; Rebstein; Remscheid; Reutlingen; Reval; Risano; Rochdale; Rockhampton; Rome; Rouen; Roux; Roxburgh; Sacile; Saigon; Sains du Nord; Saint Martin; Salina; Samsoun; Santa Ana; Santa Fe; Santander; Saxon; Scheemda; Schiedam; Schomberg; Schonheide; Semarang; Seraing; Sfax; Shreveport; Simla; Sioux City; Siveveghem; Skelleftea; Skive; Soderhamn; St Anne's Bay; St Avold; St Feliu de Guixols; St Fiden; St John (New Brunswick); Strasbourg; Stromstad; Suakin; Sucre; Sulina; Sundsvall; Svendborg; Swansea; Sybadah; Szechwan; Szeged; Taipei; Tananarive; Tandragee; Tarija; Taylor; Tellicherry; Terrell; Therezina; Thomasville; Thorn; Tiflis; Timaru; Tocopilla; Tokyo; Toowoomba; Tossa; Traben; Trapani; Travancore; Trelleborg; Tsingtau; Uddevalla; Ulrichstal; Union Beach; Vevey; Vigevano; Villers; Vilvorde; Vyborg; Wandesbek; Wanganui; Wantage; Werdohl; West Hartlepool; Whiteinch; Wiesbaden; Wilhelmsburg; Wilkes Barre; Winschoten; Winterthur; Xanthi; Zaandam; Zofingen.

Notes: This table lists all cities in the network. Cities are classified into different categories according to the number of borrowers they feature. See text.