Business Among Friends: Personal Connections and Client-Sharing in Merchant Banking, c. 1900

Aurelius Noble*

Tuesday 13th February, 2024

[Work in Progress]

Abstract

Merchant banks were hugely important in the provision of short-term credit, reducing information asymmetries between borrowers and lenders separated by vast distances. This paper looks at client sharing between merchant banks operating in the London acceptance market c. 1900. It examines the relationships with these borrowers, exploring the extent to which clients formed 'relationship banking' ties. In that model, clients form non-transferable relations with specific banks through repeated interactions. This limits the number of banking intermediaries they can access credit through. I examine this phenomenon using network analysis, showing that a large portion of borrowers actually engaged in relationships with multiple merchant banks. I introduce a new biographical dataset for 164 merchant bankers, constructing three inter-personal networks: two professional and one social. Through this I analyse the extent to which client sharing between banks related to personal ties between bankers. I find that client sharing between banks is strongly related to personal ties between bankers at those banks. This indicates that client sharing constituted some sort of collaborative arrangement. This collaboration has a number of important implications. It might reduce incentives to produce information about borrowers, as each bank can rely on other banks in their community to provide the necessary information. Broadly, it shows how personal connections shaped access to credit. If a connection to the 'right' merchant bank opened doors elsewhere, then the inverse must also have been true. Lacking these connections could result in exclusion from international capital markets.

1 Introduction

Standing before his peers in December of 1903, Felix Schuster, the president of the Institute of Bankers made a bold proclamation.

*Email: a.j.noble@lse.ac.uk. Thanks to Olivier Accominotti, Neil Cummins, Natacha Postel-Vinay and Albrecht Ritschl, and seminar participants at the LSE for their advice and suggestions.

'We are, it is admitted, the financial centre of the world; this is more than just a phrase, it is a fact' - (Journal of the Institute of Bankers, 1904, p. 58).

By 1900 the City of London was at the centre of global financial markets. The view of contemporaries was very much that London acted as a 'Bank for the whole world', from China to Germany, Argentina to the USA.[1] In particular, London provided short-term borrowing and lending facilities to actors around the globe. It became the centre of an international system of payments and trade (Chapman, 2005; Cassis, 2010; Accominotti et al., 2021). It was in this role as a global money market that London achieved its pre-eminence. Montagu Norman, Governor of the Bank of England, maintained that the City had perfected this business, and that it provided the "essential cog" for global financial machinery (King, 1936, p. xi).

At the heart of the money market were the merchant banks, who connected borrowers from around the world. The main instrument used for short-term credit was the sterling bill of exchange. These bills had a variety of functions, but they were used foremost by merchants to secure short-term credit. They would then be conveyed by merchant banks to the money market, traded, and held by other banks as liquid reserves (Jansson, 2018; Kynaston, 1996). Bills of exchange acted as near-cash assets, they were highly liquid and safe, and traded freely on the money market. These traits are particularly impressive given the vast information asymmetries that existed between borrowers and lenders. Borrowers could be situated anywhere around the world, while investors were typically based in London. Given this distance and the huge variety of borrowers requiring credit, it was near-impossible for investors in London to ascertain the risk associated with a bill.

Essentially, this paper is about the role of personal relations, collaboration and community in resolving these asymmetries. Accominotti et al. (2021) demonstrate the role of intermediaries in reducing the amount of information lenders needed about borrowers. The intermediary, known as the acceptor, would collect information about borrowers and use this to ascertain the risk associated with a particular borrower. If the borrower was judged to be sound, the acceptor would offer to guarantee their bills. With this guarantee the acceptor became liable for the bill. Consequently, their reputation was attached to it. If investors viewed the acceptor as relatively riskless, they did not need to worry about the risk associated with the original borrower. By lending their reputation to credible borrowers, acceptors signalled that a bill was safe. Moreover, by engaging in information gathering activities, acceptors rendered the bills 'information insensitive' (Gorton, 2012). That is to say, they ensured that the cost for investors of learning profitable private information about the bill exceeded any potential gains. There was no valuable information to learn about a bill and all parties knew this. This information-insensitivity meant the bills were a highly liquid asset. Yet, merchant banks frequently shared their borrowers with other banks. This paper investigates the relationship among intermediaries and between them and borrowers, to better explain how personal relations affected access to capital and information production activities.

The most common acceptors of bills of exchange were the merchant banks, who issued around 70 percent of acceptances in 1913 (Cassis, 2010, p. 85). The prestige of these firms meant that their acceptance lent particular weight to a bill. 'First-class' bills of exchange, as they were called, were viewed as virtually riskless (Kynaston, 1996). The reputation of these merchant banks relied on their ability to accurately assess risk. To this end,

[1] Nathan Rothschild cited in (King, 1936, p. 265)

merchant banks engaged in information production concerning prospective borrowers. However, their incentives to invest in information depended heavily on the structure of the market. Recent work in this field has argued that the association between merchant banks and their clients should be thought of within a 'relationship banking' framework (Accominotti et al., 2021). This framework suggests that banks will initially pay a fixed cost to gather information about a prospective client. They will then gain further 'soft-information' about that firm through repeated transactions. The unique relationship between borrowers and banks gives borrowers more incentives to share information, as they have less bargaining power, and gives banks more incentives to invest in information, as they anticipate future gains from this investment. The competitive advantage of the bank requires that three key conditions are met (Boot, 2000). Firstly, the bank is able to gather information beyond that which is publicly available. Secondly, the bank can produce information through repeated interactions with the same borrowers. Finally, the information that the bank has about the borrower is confidential. This framework means information about borrowers should be unique to each merchant bank. Consequently, the clients of each bank should be mostly distinct. Other firms should not be able to easily gather similar information about the same firms and borrowing firms should not be able to use competition between banks to avoid scrutiny.

This paper argues that while relationships with borrowers were important, so too were relations between merchant banks. Relationships with borrowers were varied. While some borrowers were unique to each bank, many had their bills accepted by multiple merchant banks. Using the sample from Accominotti et al. (2021) for 1906, I find that 52.9 percent of the clients of merchant banks are shared with other acceptors. Rather than acting as the sole acceptor for a firm, merchant banks often preferred to limit their liability to individual firms and distribute the risk. However, it was not the case that there was open competition for these clients. Given that merchant banks preferred to only provide partial credits to borrowers, they tended to share these borrowers with other merchant banks with whom they had personal ties. By reconstructing social and professioanl linkages between merchant banks, I demonstrate that the choice of shared clients was not random. Merchant banks collaborated to share clients with other merchant banks to whom they were close. This aligns with much of the historical literature on merchant banking, which suggests "competition within limits" (Cassis, 1985; Chapman, 1986; Cassis, 1988). Collaboration and community seem to have been important elements of the money market. Privileged borrowers had access to capital through a number of personally connected intermediaries. This suggests that merchant banks, the arbiters of the money market, had fewer incentives to produce novel information about borrowers. In particular, they had less reason to engage with potential borrowers who were not already known to this community. Access to capital may have been limited for those who were unable to obtain this personal element of trust.

To analyse the effect of inter-bank social and professional linkages this paper constructs several new datasets on the lives of British merchants, bankers and financiers. It uses biographical dictionaries, namely Henry Bassett's *Men of Note in Finance and Commerce* (1901) and *Who Was Who* to construct a dataset of 1,761 individuals, including 202 merchant bankers. From this I collect information on 2,524 memberships at 669 gentlemen's clubs, of which 303 memberships are those of merchant bankers. I gather further information on 6,586 memberships at 3,855 different firms, of which 907 memberships are those of merchant bankers. This is augmented with data I collect from Thomas Skinner's *The London Banks* from the same year (1901). This lists 246 banks, of which 72 are merchant banks. It contains details on 1,183 partnerships or directorships. Together these data are used to create three different networks of personal linkages between merchant banks. These networks are then compared to one constructed using data from Accominotti et al. (2021). Their dataset contains all of the bills of exchange discounted at the Bank of England in 1906. It provides information on the drawers and acceptors of bills, from which a network of shared drawers is constructed.

I find that that inter-bank connections in social and professional networks are positively related to client sharing relations between banks. The size of the effect is relatively large, an increase of 1 shared directorship at a non-merchant bank relates to an increase of 3.24 shared (and recorded) clients. Similar, smaller effects are recorded for directorship of other firms and for connections through social clubs. The median and mean number of clients appearing in the Bank of England database for these firms were 7 and 39 respectively. To test whether this outcome was the result of a random process or the structure of the network, I compare these results to two sets of simulations. These create networks with similar structures, where connections are randomly determined. Two different types of simulations are used to account for different structural characteristics of the network. The relationship between the observed networks is far greater than the relation we would expect from chance.

The structure of the paper is as follows. Section 2 details the functioning of the bill of exchange. Section 3 discusses the literature on merchant banking. Section 4 discusses the data and sources used. Section 5 examines inter-bank linkages in the bill market. Section 6 highlights the role of shared social and business interests in client sharing. Section 7 speculates about potential mechanisms for this relationship and what its effect might be on information production. Section 8 concludes.

2 Bills of Exchange

Before delving into the role of personal relations in credit provision, it is important to first understand the nature of the credit they were providing. This section, on the bill of exchange, demonstrates why acceptors needed good information on borrowers for those borrowers to be able to access financial facilities in London.

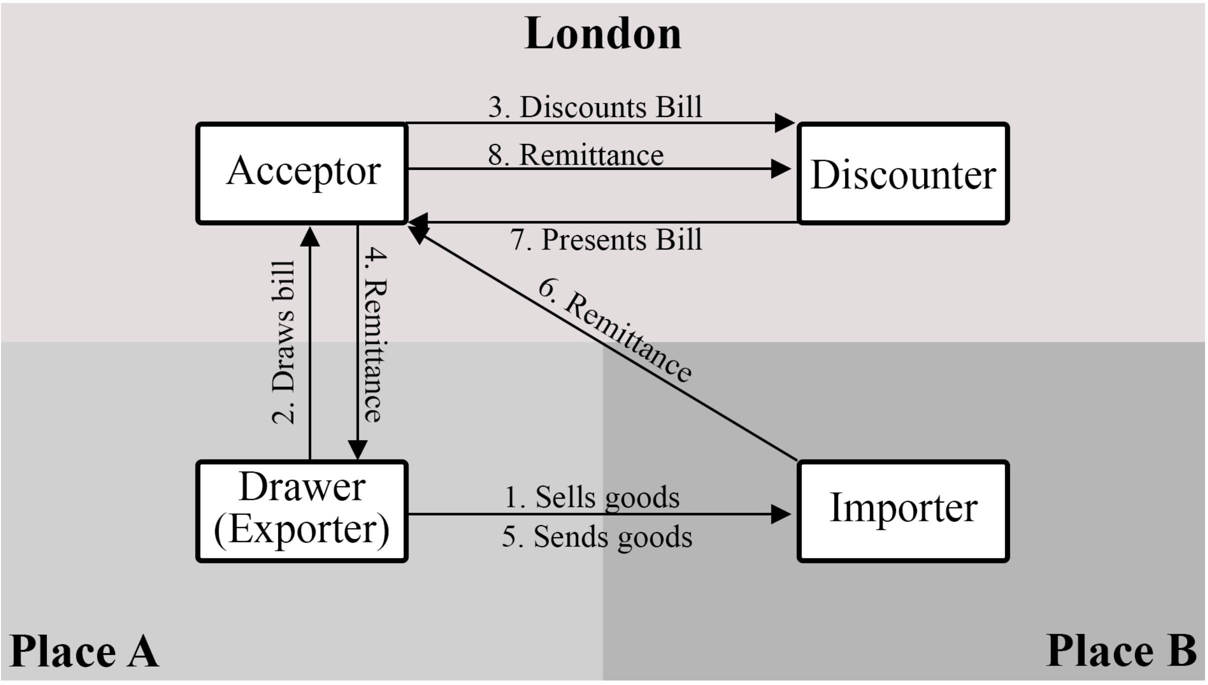
By the late nineteenth century, bills of exchange were the standard short-term debt instrument. They had a variety of functions, but their primary use was in trade credit.[2] Long-distance trade naturally resulted in uncertainties and frictions, as goods were shipped across the world. Bills of exchange acted as promissory notes, pledging to pay the holder after goods arrived. This promise was typically guaranteed by a third party, the acceptor, who became liable for payment. The guarantee of the acceptor enabled the bill to be freely traded. The bill was effectively as good as their reputation. By having public information about the reputation of acceptors in London, investors could assess the risk associated with a bill, overcoming the vast information asymmetries between them and the eventual borrower. Only the acceptor needed information about the bill or the borrower themselves. From the 1820s onwards, the role of acceptor was increasing filled by specialised merchant banks (Chapman, 2005). Their reputation as astute appraisers of borrowers meant that bills accepted by them were particularly highly valued. The bills accepted by the most prestigious merchant banks were the 'ultimate liquid asset' and were generally seen as near riskless (Jansson, 2018; Accominotti et al., 2021). Merchant banks were particularly well positioned to embrace this role because of their strong con-

[2]For a detailed history of bills of exchange see Accominotti and Ugolini (2019).

nections with overseas merchant communities. Almost all merchant banks evolved from small trading firms. For instance, Barings started as wool merchants from Groningen, Brown-Shipley as linen merchants in Baltimore, and Kleinworts as Altona merchants working in a counting house in Havana (Ziegler, 1988; Ellis, 1960; Wake, 1997). They were in a privileged position to acquire information. This paper suggests that not all of that informational advantage was from closer connections to clients or markets, but that some of it arose from ties to other merchant banks.

Figure 1 details a typical transaction financed through a bill of exchange. Bills were a highly flexible instrument and could be used in a variety of ways. The following description relates to a *bank bill* where the acceptor has also arranged discounting for the drawer. *Bank bills* were those drawn on financial institutions, such as merchant banks. A fuller description of the different uses of the bill of exchange can be used can be found in Gillett's *The Bill on London* (1952).

Figure 1: Example of a bill of exchange network



Note: Maturity is reached at step 6. These took many different forms. Here the drawer is the exporter, but it could instead be the importer. The link in step 2 is the connection I later use to construct the shared drawers network.
Source: author's own representation drawn from Gillett Brothers Discount Company (1952).

In step 1 an exporter (the drawer) in one city sells goods to an importer overseas. The exporter is not willing to send the shipment until they receive payment for those goods. Conversely, the importer is not willing to send payment for the goods until they arrive. To remedy this situation, in step 2 the drawer draws a bill on an acceptor (e.g. a merchant bank). This bill is a promise by the importer to pay the holder of the bill after the shipment should have arrived, when the bill will reach maturity. It is guaranteed by the acceptor, who will pay the holder if the importer cannot make good on their promise. The acceptor charges a commission for this guarantee and in step 3 arranges for it to be sold at a discount (i.e. discounted) to a discounter. The discounter purchases the bill via the acceptor, channelling cash down to the exporter in step 4. This gives the exporter the liquid funds necessary to ship goods to the importer in step 5. Once the shipment arrives and the bill matures, the importer makes good on their promise and sends funds to the acceptor in step 6. In step 7 the current holder of the bill presents it to the acceptor, who acts as an intermediary, channelling funds from the importer to the discounter in step 8. In this way the discounters are able to overcome the substantial information asymmetries between them and the exporter. Typically a bill would first be discounted by a specialised bill broker and then rediscounted by deposit or central banks and held as a liquid asset. In Figure 1 the drawer is the exporter, but it could instead be the importer. The shared drawer network constructed in Section 4 is derived from the relation between the drawer and the acceptor, seen in step 2. Where the drawer has multiple acceptors on different bills, these acceptors are considered to be connected by that shared drawer.

3 Merchant and Relationship Banking

Merchant banking was an arena subject to competition within limits. Failure was exceedingly rare and there were only two amalgamations of merchant banks in the 1890 to 1914 period (Cassis, 1994, p. 40). The only major crisis within the sector was the Baring crisis in 1890. Here, co-operation was the watchword of the day. The Bank of England rapidly organised a rescue operation, which included contributions from virtually all of Baring's competitors, including the Rothschilds, Glyns, Mills, Brown, Shipley, Antony Gibbs, Morgans, Hambros and Raphaels (Ziegler, 1988, p. 253-254). Moreover, the Bank of England itself had strong ties to the merchant banking community. Many, if not most, of its directors were drawn from the partners of the merchant banks, and there was a strong sense of shared community (Lisle-Williams, 1984a). The Edwardian era was primarily a period of continuity and consecration, with limited structural changes in the sector (Cassis, 1994). Throughout the period merchant banks were characterised by family-based control and private ownership (Lisle-Williams, 1984a,b; Daunton, 1988). Nonetheless, there is debate about how dynamic the sector was. While Chapman (1986) has argued that it was an era of increased competition, Cassis (1994) and Lisle-Williams (1984a) suggest the opposite. These contrasting views are driven primarily by differences in which banks are considered more important. Focusing on the newer firms, particularly Kleinworts and Schroders, Chapman (1986) contends that their rapid ascent was indicative of a broader dynamism. Conversely, Cassis (1994) and Lisle-Williams (1984a) maintain that these banks were in the minority, and that the "aristocratic core" around Barings and Rothschilds was far more influential. Taken together, despite their disagreement about how to characterise the sector, there is consensus that there existed a less competitive core and a more dynamic periphery. This core was integrated with the aristocracy and increasingly resembled a club of sorts, with close social ties between members (Cassis, 1994; Daunton, 1988). This was especially the case after the Baring crisis, the trauma of which demonstrated the perils of competition (Vedoveli, 2018; Kynaston, 1996, loc. 5731). Merchant banks respected each others territory, as Lord Revelstoke wrote in 1902 'the preserves of Brazil and Chile will be respected as belonging to our noble friends in New Court'.[3] As underwriting became more common, incentives to collaborate increased. Syndication of issues meant that banks were no longer acting en-

[3]John Baring cited in Ziegler (1988, p. 303)

tirely independently (Chapman, 2005, loc. 2024). Merchant banks engaged in numerous co-operative arrangements: issue syndication, agreements not to poach clients, respecting territorial interests, information sharing, joint control of investment funds, and joint control of other businesses (Lisle-Williams, 1984a, p. 257). The appetite for risk and competition in these firms was limited. They were oriented around the family and as limited liability partnerships were not introduced until 1907, the consequences of failure were profound (Daunton, 1988).

There were more lively actors on the scene, notably the Anglo-German arrivals Kleinworts and Schroders. By 1913 these banks had risen to the top of the league table, so to speak, with more acceptances than either Barings or Rothschilds (Chapman, 1986, p. 184). If the old, Anglicised names were part of an aristocratic community, there is little evidence these banks were. Looking at the merchant banks with over £1m of capital, at least two-thirds had no obvious aristocratic connection (Chapman, 1986; Cassis, 1988). While most of the former group had partners sitting on the board of the Bank of England, the new arrivals were barely represented. Indeed, Baron Schroder openly criticised his partner F. C. Tiarks for taking a directorship there (Chapman, 1986, p. 187). However, what is not clear is whether their success was due to violating prevailing social norms. For instance, not engaging in the same co-operative arrangements as other banks. Among the merchant banks with no aristocratic connections and a capital over £1m, only one was non-German, the Greek house Ralli Bros (Chapman, 1986, p. 181). The rise of the new Anglo-German banks is more closely related to their strong connections with emerging markets than their unwillingness to collaborate. These firms were also willing to take on more risk, raising their acceptance to capital ratios above industry norms (Kynaston, 1996, loc. 5964; Diaper, 1983, p. 78-79). So while there was a degree of dynamism, its not clear the extent to which even these banks operated in a completely non-collaborative framework. The newer entrants were important, but they were very much in a minority, and did not upset the established order (Cassis, 1988, p. 119; Kynaston, 1996, loc. 5966). The extent of collaboration and information-sharing has crucial implications for the incentive framework these banks operated in. Compared to a purer form of relationship banking, client-sharing should reduce incentives to invest in information production about clients (Boot and Thakor, 2000).

The typical model of relationship banking has a few key characteristics. Boot (2000) defines it as the provision of financial services by an intermediary who invests in client-specific information, frequently of a proprietary nature, and who assesses potential risk through multiple interactions with a client. The competitive advantage of each bank is its privileged access to information about clients, arising from a unique relation with the client developed over a period of time. This client focused approach means that lending (or in this case guaranteeing) banks do not have to probe each individual transaction to evaluate the risk associated with it. Firms pay an initial fixed cost to establish relationships and acquire new expertise, and then continuing costs are much lower (Freixas, 2005). London merchant banks were in a prime position to engage in this form of banking. They typically had international (kinship) networks, strong connections to merchant communities, relations to state actors, and access to London capital markets. A long-standing presence in foreign markets meant each bank had a competitive advantage in its area of specialisation. Clients who were loyal to them should have few incentives to engage with other banks. Relationship banking is premised on the idea that the information needed to assess a borrowing firm's quality is not easily transferred between banks or conveyed by borrowers to new bankers (Accominotti and Ugolini, 2019). This means they are, to a degree, "informationally captured" by the bank with which they have a relation (Sharpe, 1990). This non-quantitative, non-transferable information is termed "soft information". In its purest form, this model of banking suggests that borrowing is most effectively handled by a single intermediary, with no clients shared between banks.

However, many merchant firms would have been relatively large compared to the banks guaranteeing them. Chapman (2005) gives a number of examples of "typical" clients. He describes three different clients in the 1830-1900 period, the capital of which ranged from £200,000 to £470,000. None of these had unique relations with their acceptors, all drew bills from at least 3 merchant banks (Chapman, 2005, loc. 2626-2665). By his analysis, most major clients were supported by a group of merchant banks. There are various reasons why this could be the case. If merchant banks cared more about minimising risk than maximising growth, then ensuring they 'captured' a firm was less important, they would be happier to provide only partial credit. A quote from Alexander F. Kleinwort is particularly illuminating here. "We would at all times rather increase the number of our correspondents than the transactions with a few of them - large credits are desirable only when the position of the parties concerned are thoroughly known to us".[4] Banks might prefer to limit their exposure by diversifying their clients, restricting the credit given to any single client (Jansson, 2018, p. 239). Consequently, a single merchant bank could not supply all the credit demanded by a larger merchant firm. If they were going to share clients, then collaboration could help reduce the production of redundant information. The relationship banking literature does find similar effects. Smaller borrowers are much more likely to engage with only one lender, while larger firms are more easily able to convey information about their quality to other banks without long-standing relationships (Petersen and Rajan, 1994). Further, as the duration of a client-bank relationship increases, if other banks are aware of this relation, it can signal higher firm quality (Farinha and Santos, 2002). At the very least, this could help reduce search costs. That's not to say the relationship banking did not apply at all to merchant banking. As Accominotti et al. (2021) have shown, acceptors did invest in client-specific soft-information about borrowers, with whom they engaged in longstanding relationships. However, the nature of these relationships was varied. They note that 40 percent of acceptors in their dataset did not share any drawers. However, if we only consider merchant banks this drops to 12 percent. On average, merchant banks shared 52.9 percent of their clients with other acceptors.[5] While they enjoyed unique relations with many drawers, clearly shared clients were also a key part of their business.

The contention of this paper is that clients were not shared randomly, their relationship was not to a single merchant bank, but to several connected merchant banks who pooled some of their information. Obviously this was the natural *modus operandi* in issuances, the other major area in which merchant banks operated. Recent work on the Baring crisis suggests that syndication agreements were strongly related to personal (*philos*) ties between issuing parties (Vedoveli, 2018). Barings struggled to gain reliable information even in the area of its supposed specialisation, Argentina. Its primary agent in Buenos Aires, Nicholas Bouwer, only formed weak connections with Argentine actors, and remained highly embedded in the expatriot community. Barings received conflicting information and could not be certain about whether they could trust him, as he developed strong ties with other Anglo-Argentine firms. Instead, it came to rely on co-operation with other banks involved in the area. This was facilitated by Hermann Hoskier, who had personal relations with the partners and directors of Barings, Hambros, Brown, Shipley,

[4]Alexander F. Kleinwort, cited in Chapman (2005, p. 75)

[5]Full details on this are given later in the paper.

and Paribas. Though the structure of underwriting was different, involving several parties in the same transaction, there are clear lessons here. Where information acquisition was difficult and risk sizable, merchant banks organised risk sharing agreements through their personal connections. Its difficult to establish the novelty of these co-operative arrangements. Perhaps earlier merchant banking was characterised by a more relational structure. In previous periods London merchant bankers would have been recent immigrants, with stronger connections to overseas communities. Chapman has argued that it was the age of the telegraph that ended the 'dispersed family' model, shifting the paradigm towards actors who were more flexible, with the ability to move around and form new connections (Chapman, 2005, loc. 1181).

4 Data

4.1 *The London Banks*

To identify merchant banks, I use the database constructed in Noble (forthcoming). This employs Thomas Skinner's *The London Banks and Kindred Firms*, a business directory published between 1865 and 1916. The directory contains the names of all partners and directors of all London banks, as well as the type of bank and the year it was established. This is the most definitive source on London banks and bankers and contains a wide array of firms. Banks included in 1901 range from Economic Bank, Ltd. with £7,229 of paid-up capital, to the Bank of England, with £14.6m. For this paper the sample I use is merchant banks from 1901, of which there are 72. There are 232 partners listed for these firms. The names of the firms and their members are hand-matched with the following sources. I also use data on partnerships and directorships of non-merchant banks, from the same source and year, to identify other banks where merchant bankers acted as partners or directors. There are 176 other banks listed, with 944 directors and partners. These are used to create an inter-bank network of shared partnerships and directorships (Figure 3). The network of shared bank directorships, therefore, does not measure whether merchant banks shared partners with each other, this was not the case. Instead, it measures whether the partners of two separate merchant banks acted as partners or directors at another, non-merchant bank. It is not measuring direct economic ties between the two merchant banks, but the extent to which partners from different merchant banks knew each other personally through partnerships or directorships elsewhere in the banking sector.

4.2 *Men of Note in Finance and Commerce* and *Who Was Who*

Individual level data on the social and professional lives of merchant bankers is collected from Herbert Henry Bassett's (1901) *Men of Note in Finance and Commerce*. This was intended as an ongoing series, containing biographical details on prominent individuals engaged in finance and commerce. Ultimately, only one edition was published, in 1901. It was modelled on other successful biographical dictionaries, notably *Debrett's Peerage* and the more recent *Who's Who*. Information was gathered from a variety of sources: statesmen, professional bodies, newspapers, and the individuals concerned. Its stated intention was to provide a representative depiction of the sector. The biographies within gives details on: birth-place, birth-year, education, career, titles, social life, and residences. A small sample of entries are shown in Figure 2.

Figure 2: Sample entries from *Men of Note in Finance and Commerce*

ADAM, Lord. James Adam. Judge of the Court of Session. Born at Edinburgh on October 31, 1824. Educated at Edinburgh Academy and University. Extraordinary director of British Linen Company Bank; Edinburgh Life Assurance Co.; Scottish Equitable Life Assurance Society; and Scottish Widows' Fund Life Assurance Society. Member of Athenæum Club. Residence: 34, Moray-place, Edinburgh.

ADAM, A. Chivas. Born at Aberdeen, 1844. Educated at Banff and Aberdeen. Entered business in 1860, and became a partner in Adam & Co.; is now partner in Adam & Co., Aberdeen, and Adam Brothers, of London, steamship owners. Director of Adam Steamship Co., Sunderland Shipbuilding Co., London Graving Dock Co., and Mutual Steamship Insurance Association. Member of Conservative Club and City of London Club. Business Address: 17, Gracechurch-street. Residence: Hethersett-lodge, Putney.

ADAM, Sir Frank Forbes. C.I.E.

ADAMSON, William. C.M.G. Born 1832. Educated privately. Carried on business for many years as a merchant in the Straits Settlements, and is now head of the firm of Adamson, Gilfillan and Co., East India merchants. Is a member of the London Committee of Yangstye Insurance Association; chairman of the Straits Settlements Association; and director of Peninsular and Oriental Steam Navigation Co. Business Address: 2-4, Billiter-avenue, E.C. Residence: Rothbury, Avenue-road, Highgate, W.

ADDINGTON, Lord. Egerton Hubbard. V.D.; M.A. (Oxon.); J.P. and C.A. (Bucks); M.P. for Buckingham (1874-80), and N. Bucks (1886-9). Born 1842. Partner in firm of John Hubbard and Co., Russia merchants. Director of Royal Exchange Assurance Corporation and Surrey Commercial Dock Co. Member of Carlton Club. Business Address: 4, St. Helen's-place, E.C. Residence: 24, Prince's-gate, S.W.; Addington Manor, Winslow.

Source: Bassett (1901, p. 18).

There are six different "lists" contained within the dictionary, with varying amounts of detail. This paper uses the "General List", containing details on the partners and directors of financial and commercial firms.[6] In total this list includes 1,693 biographies, of which 91 are listed as merchant bankers in Skinner's *London Banks* directory. From these biographies I collect the names of firms where listed individuals were partners or directors and the social clubs they were members of. In total I collect details on 3,699 firms and 262 clubs, for which there are 6,394 and 1,793 memberships recorded, respectively. The names of firms and clubs are cleaned and then matched by hand. The sample used in this paper includes members of the merchant banks listed in Skinner's directory. These biographies are augmented with similar data collected from *Who Was Who*. Here I search for all partners of merchant banks listed in Skinner's directory. This includes additional biographies for 73 individuals, and concerns 147 firm memberships and 143 club memberships. These sources are combined to create two separate inter-bank networks, one based on shared social clubs and one based on shared directorship or partnership of businesses (Figure 3).

Naturally, these biographies focus on the most prestigious individuals. Consequently, the social and professional connections captured here represent the upper-tail. They contain information on the individuals who are the most professionally and socially promi-

[6]Other lists focus on bank managers, officials of the London Stock Exchange, managers and actuaries of insurance firms, members of the Institute of Civil Engineers, financial publications, and officials. Though these lists are significantly less detailed.

nent. Nonetheless, of the 15 merchant banks with a pre-war capital of over £1m, only one, Raphael & Sons, is not represented in these sources. Consequently, the effect this paper captures directly is only the effect of ties between prestigious bankers, though most merchant banks have several partners who fall into this category.

4.3 Bank of England Discount Ledgers

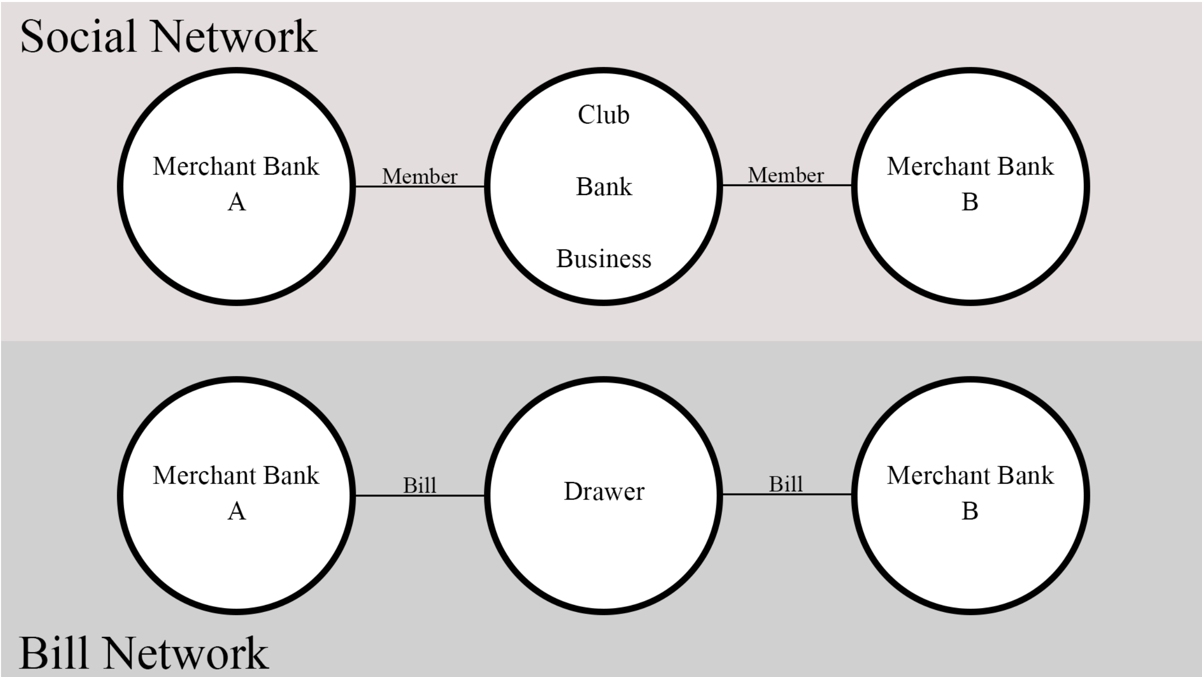
Finally, I use data on acceptors and drawers from Accominotti et al. (2021). These data give information on a variety of acceptors and drawers. For this paper, I focus on the merchant banks found in this dataset, who are hand-matched with my other sources. These are used to create a network of shared drawers (i.e. clients) between the merchant banks (Figure 3). The source they use is the Bank of England's *Discount Ledgers* from 1906. As bills were discounted in the London money market, many ended up in the Bank of England's reserves. In total, they record the details of 23,493 bills, and 4,970 firms. Of these, 3,554 are drawers, 1,439 are acceptors, and 145 are discounters. The ledgers record the details of the drawer, acceptor and discounter connected to the bill.

While these ledgers are the most comprehensive source on the bill market, they certainly don't constitute its entirety. The discount ledgers nonetheless seem a relatively representative source of information on acceptance. Comparing the number of bills accepted by each acceptor in this dataset, with aggregate data on total acceptances given by Jansson (2018, p. 268), the rankings produced are almost identical. Similarly, the breakdown of different types of acceptor found in the Bank of England ledgers is very similar to that found at another major discounter, Gillett Bros. & Co (Accominotti et al., 2021, p. 13-16).

4.4 Network Construction

These four different sources are used to create four different networks of ties between the 72 merchant banks. In each network, the ties between the banks are weighted by how many connections they have between them. The construction process of each network is shown in Figure 3. A shared bank directorship/partnership network is created by counting the number of times partners of each merchant bank share a directorship/partnership at a non-merchant bank, using *London Banks*. A shared business network is created by counting the number of times partners of each merchant bank share a directorship/partnership at any other firm, using *Men of Note* and *Who Was Who*. A shared social network is created by counting the number of times partners of each merchant bank share a social club, using *Men of Note* and *Who Was Who*. A shared client network is created by counting the number of times each merchant bank shared bills from the same drawer, using Accominotti and Ugolini (2019). The process for this is simple. Taking the example of the bill network. I select all bills accepted by a given merchant bank A. Then I check the names of the drawer on each bill. I take the list of unique drawers and select all the bills they appear on. Then I check the names of all the merchant banks acting as acceptors on these bills and create a tie between each of these merchant banks and the originally selected merchant bank.

Figure 3: Network construction procedure diagram



Note: Each of these structures is converted into a single, weighted tie between each merchant bank. Through this process I create four separate networks. The first is weighted by how many club memberships partners of two separate merchant banks share. The second is weighted by how many directorships of non-merchant banks partners of two separate merchant banks share. The third is weighted by how many directorships or partnerships at other firms partners of two separate merchant banks share. The fourth is weighted by how many drawers two separate merchant banks share.

5 Client Sharing

The main empirical element of this paper examines why merchant banks shared drawers with each other. Before moving on to this, it is important to first establish the extent of client-sharing using the bills of exchange network. The traditional relationship banking model suggests this should be minimal. Each bank gains a competitive advantage through their relation with the client. They have few incentives to share, and the client is unknown to the vast majority of lenders. The only banks willing to engage with drawers do so because they hold privileged information about the firm. There are 3,554 drawers in the Bank of England database (from 1906), but Accominotti et al. (2021, p. 19) focus on the 1,381 who appear on more than one bill. They do so because drawers who are only documented once cannot inform us about network structure. By construction, these will only be connected to one acceptor (and discounter). Consequently, there cannot be an imbalance in how many acceptors or discounters are associated with that client. Nor is it possible for acceptors to share these clients between them.

If we look at the drawers whose names appear on more than one bill, we find that on average they had 2.83 acceptors. Without much in the way of a reference, it's difficult to ascertain the extent to which this matches the relationship banking model. The figure is situated perfectly between two extremes. On the one hand, if banking were purely relational and each drawer could only gain acceptance from the one bank able to effectively gather information about them, then this figure would be one. That is, each drawer would only have one acceptor. On the other hand, if banking were purely transactional, and clients selected acceptors at random, then for each client the maximum number of acceptors is simply the number of bills they have accepted. On average this is 4.86 bills.

Does this mean that acceptors did not play an important role in resolving information asymmetries? Clearly not. The central empirical component of Accominotti et al. (2021) compares simulated bill of exchange networks to the one observed in the Bank of England ledgers. Effectively, they take all drawers, acceptors and discounters, and randomly distribute connections between them, keeping the same number of connections and the same demography. They demonstrate that the distribution of connections in the network is weighted more heavily towards those between acceptors and discounters than would be expected randomly. That is, given the number of drawers, acceptors, and discounters in the network, there are a smaller number of drawer-acceptor ties and a greater number of acceptor-discounter ties than expected. This suggests that acceptors resolved information asymmetries. If this was a random process, then the smaller number of discounters in the network would mean that very few drawers would be connected to more discounters than acceptors. Drawers are guaranteed by only a small number of acceptors, but receive funds from a large number of discounters. This demonstrates that acceptors provided information which allowed for a greater number of investors. However, this simulation only concerns the distribution of ties, rather than their raw number. The model has to assume a fixed number of connections in the network. This means that the average number of ties each actor has is fixed. If we wanted to assess the degree to which this was relationship banking, we would want to know whether the number of ties between drawers and acceptors is less than expected. Isntead, we only knew there are fewer drawer-acceptor connections relative to drawer-discounter connections.[7] Though this model shows that acceptors reduced information asymmetries, it does not tell us about the efficiency with which they are doing so. Rather than pure relationship banking, where a single drawer is connected to a single acceptor, we often see a drawer connected to a cluster of acceptors.

Thus far, we've viewed this issue entirely from the drawer's perspective. However, the picture is significantly different from the acceptor's angle. A surprisingly large portion of acceptors share their drawers with other banks. In part this is driven by something known as the 'friendship paradox' (Jackson, 2019, p. 13). The paradox is that on average peoples' friends have more friends than they do. The intuitively deceptive nature of this paradox quickly gives way to a quite shallow explanation. Popular individuals show up on more people's friendship lists, so they are sampled more frequently. Thus, on average, each persons' list of friends overly reflects popular people. Similarly, drawers who are connected to many acceptors show up on the bills of many different acceptors, connecting them to many other acceptors. A relatively large portion of acceptors, 59.6 percent, share drawers with other acceptors. This is much more common among larger acceptors. Of those accepting more than one bill 78.2 percent share drawers and at more than 5 bills this is 92.1 percent.[8] For the 53 merchant banks appearing in the Bank of England's discount ledgers, 88.0 percent shared clients with other acceptors. On average, these banks share 52.9 percent of their clientele with other acceptors. It seems that shared clients constituted the more significant part of the business of these banks.

The literature on merchant banking suggests that there was a non-competitive, en-

[7] Drawer-discounter connections through an acceptor.

[8] This is not the total number of bills that acceptor is accepting in 1906, just those which show up in the Bank of England ledgers. As such, it may be measuring prestige rather than size, though there are reasons to think the composition of bills is representative, see the Data section.

Table 1: Merchant banks' shared drawers, by foundation date

Founded	N	Mean (%)	St. Dev.
Post-1850	23	44.6	32.1
Pre-1850	30	58.4	23.2

Note: This table gives the percent of drawers of each merchant bank whose bills were also accepted by other acceptors. It details the average for merchant banks founded before and after 1850. This is given for the 53 merchant banks who appear in Skinner's directory and the Bank of England's discount ledgers.
Source: Accominotti et al. (2021), and Skinner (1901).

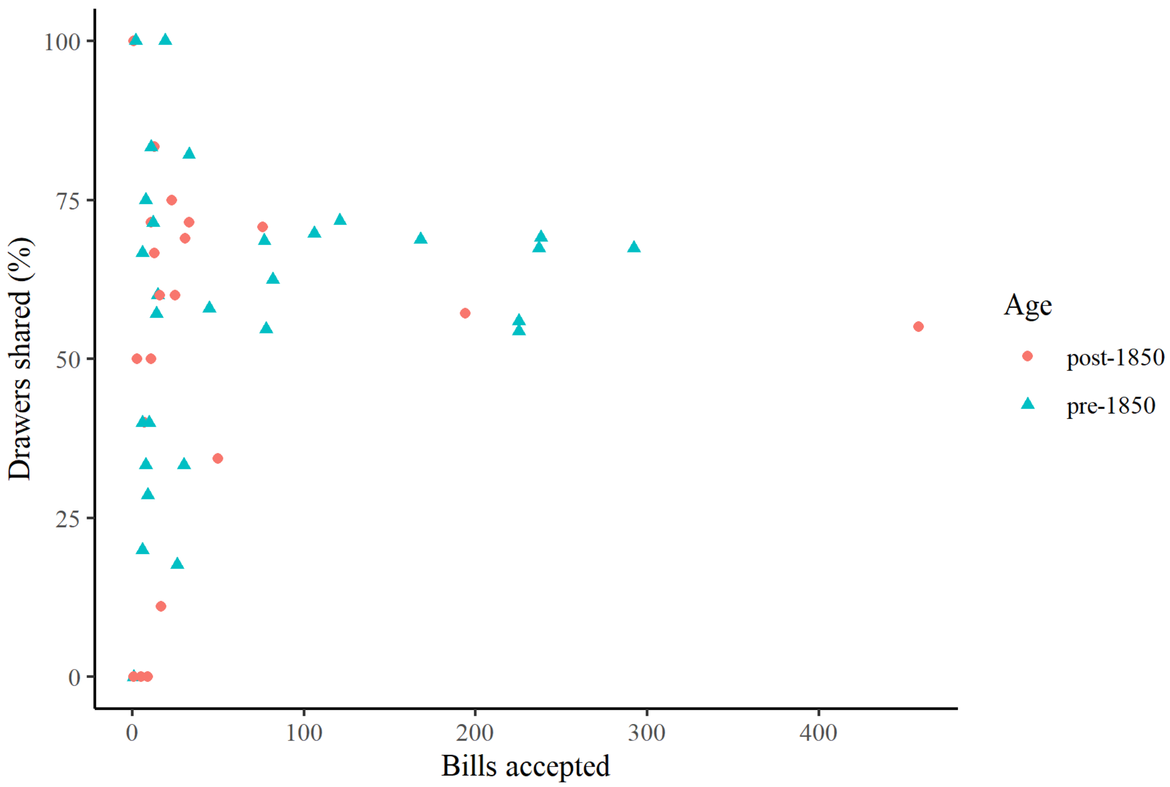
trenched core. This is where we would expect to see most of the client-sharing. If the older merchant banks formed a unified aristocratic community, which did not compete internally, then they would have fewer incentives to maintain single-client relations. The new merchant banks, on the other hand, would not have the social capital or connections to gain clients through this community.

To examine this effect, I split the sample into those banks founded before and after 1850. The cut-off is naturally somewhat arbitrary, but it neatly segments the banks into those typically described as being in the aristocratic core versus those belonging to the newer immigrant wave. Table 1 shows the extent to which this dichotomy holds. The proportion of shared clients is marginally higher for older banks, at 58.4 percent compared to 44.7, but this difference is not significant. The variation within each group is very large and no clear patterns emerge. If there was socially driven client sharing, it does not fall into these broad communities. The collaborative mechanics behind client sharing applied to all merchant banks of a certain size, regardless of their origin.

The simplest alternative hypothesis here is that client-sharing related to the size of the bank. There are various reasons why larger banks might be more inclined to share clients. Relationship banking might well be subject to diseconomies of scale. The type of personal, soft-information, required is not easily collected or organised *en masse*. It may be hard to expand the personal relations of a bank beyond a certain point. There are limited numbers of viable clients in each region, and as banks get larger they might be tempted to move outside their specialisations. The relationship between the number of bills accepted by a merchant bank and the proportion of their drawers whom they shared with other acceptors is plotted in Figure 4. As discussed in the data section, the frequency with which an acceptor appeared in the Bank of England's discount ledgers is a reasonable proxy of their acceptance volume. However, there is no clear relation here. There does seem to be some cut-off point after which sharing becomes much more common. All of the banks which appear on more than 50 bills share more than half of their clients. Nonetheless, this does not provide a satisfactory explanation of client sharing. The data is almost normally-distributed, so these patterns may be explained partially by having few bill observations for certain banks. Nonetheless, it seems like very small acceptors were less likely to share.

Having demonstrated the extent of client sharing, the next section of the paper delves into the choice of who to share clients with. Personal relations between banks, either professional or social, are related to which banks shared drawers with each other.

Figure 4: Merchant banks, proportion of drawers shared by bills accepted



Note: This figure plots each merchant bank and shows the percent of their drawers they shared with other acceptors against the number of bills they accepted in the Bank of England discount ledgers.
Sources: Accominotti et al. (2021), and Skinner (1901).

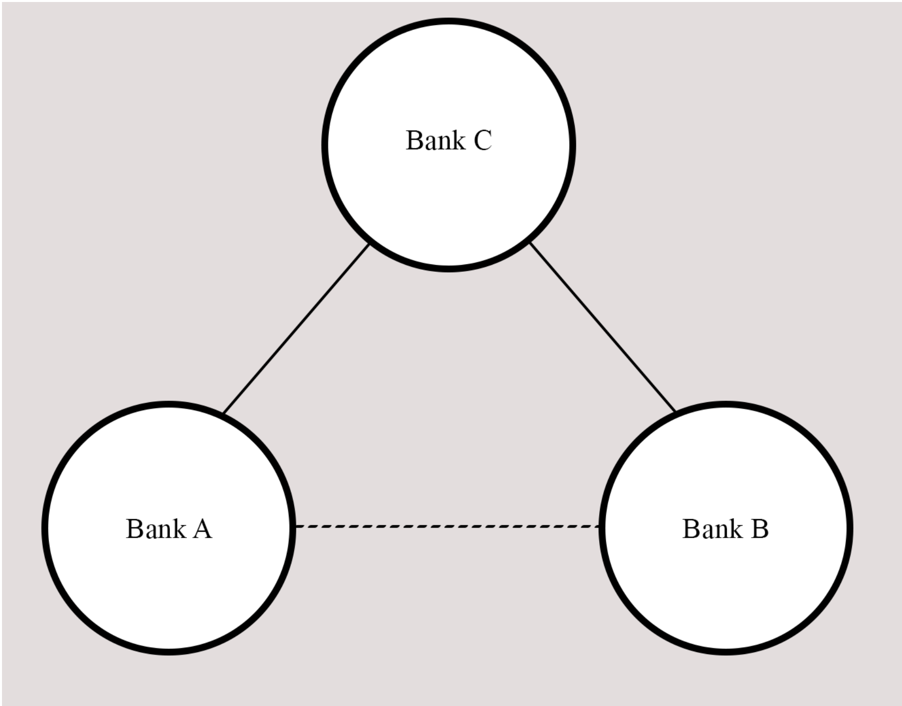
6 Personal Connections Between Merchant Banks

This section of the paper seeks to explain drawer sharing through micro-level processes, namely interactions between the merchant banks. First it examines merchant bank cliques shown by the bills of exchange data, and then it looks at how personal connections were related to sharing drawers. I argue that ties were not formed at random, but arose from the mutual interests of partners at different merchant banks. These banks formed little client sharing cliques.

The simplest test for the existence of these cliques is to look at the clustering coefficient in the shared drawers network. The clustering coefficient measures the extent to which two banks which share drawers with a third bank are likely to share clients with each other. Formally, it is the number of closed triads in the network over the number of open or closed triples, shown in Figure 5. Here Bank A and Bank B are connected to Bank C, forming a triple of three connected nodes. If Bank A and Bank B are connected (the dotted line) then this forms a closed triad. If they are not connected, then it is just a triple. The clustering coefficient for the shared drawers network is 0.64. This means that 64 percent of banks who shared a drawer with a third bank, also shared a drawer with each other.

To assess whether this clustering coefficient was the result of chance, I compare it to two different sets of simulations. The network we are comparing to contains 72 merchant

Figure 5: Clustering coefficient diagram



Note: The solid black lines show a connected triple, that is three different actors who are connected to each other. The dotted black line shows triadic closure. Clustering means that Banks A and B, who are both connected to C (the solid lines) are also connected to each other (the dotted line). For full details on the calculation of the clustering coefficient, see Appendix B.

banks (or nodes). It contains 250 connections between these banks (or edges), which are created whenever a bank shares a drawer with another bank. These are weighted by the number of shared drawers each bank has, but that is not used here. I generate 1,000 networks, which contain the same number of nodes and edges as the merchant bank network. These simulations allow me to control for the structural characteristics of the network which could lead to higher clustering.

In Simulation 1 we randomly sample pairs of nodes (without replacement) and distribute the 250 edges between them. This provides a lower-bound estimate for what we would expect clustering to look like if sharing drawers arose completely from chance. This only controls for the density. In Simulation 2 the 250 edges are distributed such that each node has the same number of total connections as in the observed network, but they are rewired to connect with different nodes (see Appendix D for details of the simulation procedure). It could be the case that having several very well-connected nodes brings up the clustering coefficient, because these nodes are quite likely to all be connected together. Simulation 2 controls for this structural characteristic of the network. The results are shown in Table 2.

These results show that clustering is much higher than we would expect in random networks with similar structural characteristics. Merchant banks are much more likely to share drawers with other banks who are also connected to the same clique of client-sharing. Clustering in the completely random Simulation 1 is much lower, at only 0.10. The coefficient is higher in Simulation 2, where the number of banks connected by shared clients is held fixed for each bank, but it is still significantly lower than the observed

Table 2: Merchant bank shared drawer clustering, simulations

	N	Mean	Standard Error	Max.	Min.
Observed	1	0.64	0.00	0.64	0.64
Simulation 1	1000	0.10	0.00	0.13	0.06
Simulation 2	1000	0.38	0.00	0.46	0.33

Note: This table compares the clustering coefficient in the observed network, with the average clustering coefficients for two sets of simulated networks, each containing 1,000 simulations. For details on the simulation procedure see Appendix D. The standard errors are given for transparency, but are basically arbitrary. They depend heavily on the number of simulations run.
Sources: Various, see Data section.

Table 3: Network summary statistics

Network	Banks	Edges	Density	Degree	Clustering Coef.
Drawers	72	250	0.10	6.94	0.64
Banks	72	53	0.02	1.47	0.91
Businesses	72	252	0.10	7.00	0.67
Clubs	72	180	0.07	5.00	0.54

Note: The number of edge is the non-weighted number of connections given by the network construction process, see Section 2.4.4 Network Construction. Density is the number of observed ties over the maximum possible number of ties, i.e. if all banks were connected to all other banks in each network. Degree is the average number of other banks each bank is connected to. The clustering coefficient is explained in Appendix B.

value at 0.38 compared to 0.64. Higher clustering in this simulation suggests that a sizable portion of clustering comes from better-connected individuals. So, banks who have many connections are more likely to share their connections with each other.

Next, I present the central empirical component of this paper. I construct three further networks based on the same set of 72 merchant banks. The first of these looks at whether the partners at merchant bankers acted as partners or directors together at other non-merchant banks. This connects the two merchant banks through a shared interest in that third bank, and a personal tie between the partners who worked there. The next network looks more broadly at professional interests. It checks whether the partners of merchant banks worked as directors or partners at any other firm listed in *Men of Note* or *Who was Who*. The biographical entries there list all the firms an individual was engaged with. There is a relatively broad array of firm types listed, ranging from mining companies to investment funds. The final network constructed uses the same sources to examine whether partners of merchant banks shared memberships at gentlemen's clubs. These clubs constituted a significant component of the social lives of their members (Noble, forthcoming). By examining the overlap in these networks, I aim to determine the extent to which personal relations, both professional and social, are linked with client-sharing.

Summary statistics for these networks are presented in Table 3. They are all weighted networks. So if, for instance, Bank A shares 5 drawers with Bank B, then the value of that edge will be 5. The only notable difference between these networks is that far fewer shared memberships of non-merchant banks are recorded.

First, I examine the extent to which bill sharing was related to prestige or social

Table 4: Network centrality correlations

Type	Banks	Businesses	Clubs
Degree Centrality			
Degree	0.52	0.32	0.31
Betweenness	0.55	0.37	0.23
Eigenvector	0.32	0.20	0.19
Matching Centrality			
Degree	0.52	0.32	0.31
Betweenness	0.26	0.02	0.09
Eigenvector	0.48	0.32	0.19

Note: This table gives the correlation between the centrality measures for each bank in the different networks. The "Degree Centrality" section of the table compares the correlation between each centrality type in the personal network and degree centrality in the Bills network. The "Matching Centrality" section of the table compares the correlation between the same centrality type in the personal and bills network. For details on centrality measures, see Appendix C.
Sources: Various, see Data section.

capital. As mentioned earlier, while the biographical dictionaries may not capture all of these ties, they should indicate the most socially prestigious individuals. If banks are well-connected, then this should be apparent from the connections between prominent individuals at those banks. To check for this I compare centrality measures between the different networks. I initially compare different measures of centrality in the personal networks with the number of shared drawers in the bill network (degree centrality). This demonstrates the extent to which different forms of prominence in personal networks related directly to bill sharing. Next, I examine the extent to which different centrality measures in the personal networks relate to those same centrality measures in the bills network. This informs us about the extent to which certain positions in the personal networks related to similar positions in the bill sharing network.

I use three different types of centrality measure. The first is degree centrality, which measures how many connections each node has. The next is betweenness centrality, which measures the extent to which nodes lie on the shortest path between nodes. This means they are likely to be conduits of information, or act as bridges or gatekeepers between different communities (Granovetter, 1973). Finally, I use eigenvector centrality. This is a more global extension of degree centrality, which only measures directly connected nodes. Instead, it measures how well connected each node is to other well connected nodes. In this was it measures the extent to which a node is embedded among other popular nodes. For further details on centrality measures see Appendix C. I first check the correlation of each of these centrality measures in the personal networks with degree centrality in the bills network. I then check the correlation between each of these centrality measures in the personal networks with the matching centrality measures in the bills network. The results are shown in Table 4.

These show a strong relationship between prominence in the personal networks, and drawer sharing with other merchant banks. This is particularly true for individuals who serve as directors for several other banks, many of whom acted as directors for the Bank of England. The correlation between the number of direct connections (degree centrality) in the bills and bank directorship networks is 0.52. Drawer-sharing is also higher in banks which are directly connected to other merchant banks through social clubs, with a correlation of 0.31. This could either be as a result of being part of a more settled, less competitive community, or because this directly enhanced the opportunity for information sharing. The correlation between betweenness centrality and the number of shared clients (degree centrality) is also very high. This indicates that merchant banks which were important in providing personal connections between distinct merchant banking communities were more likely to share clients. However, it is not the case that a bridging role in personal networks related closely to a bridging role in client sharing networks. When looking at the correlation between matching centrality types, the relation is strongest for degree and eigenvector centrality. These are both measures of popularity, prominence and embeddedness. They suggest that being near the core of the personal community meant being more central to client-sharing arrangements. Interestingly, this correlation is not as high for betweenness. This means that banks which bridged different personal communities did not link weakly connected client-sharing groups. Instead, playing a personal bridging role was more closely related to higher client sharing overall.

Next, I test the extent to which specific relations in the personal network are connected to specific relations in the shared drawer network. There are strong reasons to suspect that sharing financial interests might create incentives to collaborate. Individuals with personal connections are more likely to spend time together, and they might be more prone to engaging in other business deals. There could be a sense of trust between them that makes reciprocity more likely (Granovetter, 2017, p. 56). Further, if merchant banks were frequently reticent to fully take on clients, then collaborating to share clients is more efficient than each bank having to search out those clients. This simple explanation could be sufficient. Socially proximate bankers talk to each other. This doesn't have to provide detailed information, but could easily reduce search costs. A similar, albeit weaker, effect could be expected from sharing clubs. These individuals would probably spend less time together and have fewer interests in common than co-directors, however it suggests they moved in the same social circles.

To test for this relationship, I take the weighted adjacency matrix for each personal network and check its correlation with the weighted adjacency matrix for the shared drawers network. The adjacency matrix simply measures whether a Bank A has a connection with Bank B (for network notation see Appendix A). Typically, this would be either a 0 (no connection) or a 1 (connection). However, here it is weighted by the number of times those banks are connected. This can be illustrated with a brief example. Say we only have three banks A, B and C and two networks, the shared drawer network and the club network. Let's say A and B share 2 drawers, B and C share 0 drawers, and C and A share 4 drawers. Then A and B share 4 club memberships, B and C 0 club memberships, and C and A 8 club memberships. I vectorise this adjacency matrix, and then calculate the Pearson correlation coefficient between these two networks, so between the two lists $(2, 0, 4)$ and $(4, 0, 8)$, giving a coefficient of 1.00.

This method shows a positive correlation between the shared drawers network and the banking, business and club networks. The correlations between them are 0.21, 0.14, and 0.10 respectively. These effects suggest that personal connections have a sizable connection to client-sharing. In raw terms, an increase of 1 shared bank, business or club membership is related to an increase of 3.23, 0.64 and 0.38 shared clients, respectively. This can be compared to the median or mean number of shared clients in the observed network, which are 7 and 39. It's difficult to identify causality here, it could be that banks which share a greater number of clients are more likely to engage in the same communities. However, the key takeaway is that business appears to have been conducted along personal lines.

Table 5: Network tie correlations

Type	N	Mean	Standard Error	Max.	Min.
Bank Memberships					
Observed	1	0.21	0.00	0.21	0.21
Simulation 1	1000	0.00	0.00	0.12	-0.02
Simulation 2	1000	0.08	0.00	0.29	0.00
Business Memberships					
Observed	1	0.14	0.00	0.14	0.14
Simulation 1	1000	0.00	0.00	0.09	-0.04
Simulation 2	1000	0.05	0.00	0.17	-0.01
Club Memberships					
Observed	1	0.10	0.00	0.10	0.10
Simulation 1	1000	0.00	0.00	0.12	-0.03
Simulation 2	1000	0.03	0.00	0.15	-0.02

Note: This table compares correlations between adjacency matrices in the observed and simulated networks. For each network type, Drawers, Bank Directorships, Business Memberships and Club Memberships, I simulate 2,000 networks. 1,000 networks for each are simulated using the Simulation 1 procedure and 1,000 using the Simulation 2 procedure, for details see Appendix D. To calculate the tie correlation, I take the adjacency matrix from each personal network and the adjacency matrix from the Drawers network, and calculate the correlation coefficient between them. This shows the extent to which a tie in the Drawer network between Bank A and Bank B is matched by a tie in a personal network. For example, if we had a network of only 3 banks, and Banks A and B shared 2 drawers and 4 club memberships, Banks B and C shared 0 drawers and 0 club memberships, and banks C and A shared 4 drawers and 8 club memberships, the tie correlation between the Drawer and Club network would be 1.00. The "Observed" rows give the coefficients between the observed networks; the simulation rows give the average coefficient between the different networks over the 1,000 rounds of simulation. The standard errors are given for transparency, but are basically arbitrary. They depend heavily on the number of simulations run. The full distribution of results for the simulations can be seen in Appendix F.
Sources: Various, see Data section.

Next, I investigate the size and significance of this relationship by comparing these network correlations to those between randomly generated networks with similar characteristics. It could simply be that individuals who are highly connected in one network are highly connected in others as a result of network structures or the sampling process. By using simulations I can address this issue. I generate 4,000 networks in two different sets of simulations (see Appendix D for details). In each round of simulation I generate 1,000 networks of each of the four types (bills, banks, firms, and clubs). These are given the same number of nodes, number of edges, and demography as the observed networks of that type. In Simulation 1 the edges and weights are redistributed to random pairs of nodes. In Simulation 2, the number of connections each node has is held constant, as are the weights associated with each connection.[9] This controls for the potential that the effect is driven by similarly well-connected banks across the networks. The results are shown in Table 5.

The relation between sharing drawers and sharing social connections is significantly higher in the observed networks than simulated ones with the same structure. On the surface it seems that the strongest effect is sharing directorships of other banks. This

[9] The weights for the overall edges are not kept exactly constant, instead the half-weight for the half-edge is kept constant. This is explained in Appendix D.)

seems reasonable. Shared interests in the banking sector might promote more direct financial interests, or at the very least, more extensive discussion of financial topics. To some extent these effects are difficult to disentangle. There is a high correlation between these other networks, notably between the bank and firm network at 0.41 and the firm and social network at 0.49. This is hardly surprising. If bankers are personally related in one aspect, they are likely to be connected elsewhere. It would be a little hasty, therefore, to suggest one of these networks is the overwhelming driver of client sharing. Instead, these relations combine to show that in a number of measurable ways, personal connections mattered. They extended beyond the private lives of these bankers and affected the extent to which they engaged with other banks in client selection.

The next, more speculative, step is to see if these communities can be identified. As mentioned earlier, the merchant banking literature has often divided these relations into two relatively distinct communities: the Anglicised, aristocratic banks and the new, foreign arrivals. The network literature uses a number of approaches to try and detect communities algorithmically. One of the most commonly used means of doing so is clustering by edge betweenness. To calculate edge betweenness you take every pair of nodes in the network and check the shortest path between them. The number of shortest paths that each node lies on is called its betweenness (for details on betweenness see C). For weighted graphs, the weights are used to alter the lengths of the path. So, if two nodes are connected by an edge with weight 1, this is considered half as far as traversing an edge of weight 2. The basic principle here is that edges which act at the only conduit between groups of nodes have a high betweenness value. A high proportion of the shortest paths in the network have to run through that node, because there are no alternative bridges across groups.

The edge betweenness clustering algorithm uses this to disconnect weakly linked communities. It repeatedly removes the highest betweenness edges, creating smaller and smaller subgraphs of nodes which are connected to each other, but not to other sets of nodes. This tree-like structure, which shows the groups as edges are continually removed, can be shown as a dendrogram, as shown in Figure 7.

Community detection does show a small number of persistent cliques. For instance, Baring Brothers & Co., Arbuthnot, Latham and Co., and Frederick Huth and Co. These firms fall pretty neatly into the “aristocratic core”. They were all founded before the 1850s and partners the first two both served as governors of the Bank of England. The Rothschilds are almost always part of the main community, with the exception of the bank directorship network. However, generally the picture is far more complex, showing a number of overlapping interests and groups. These groups do not neatly follow the lines identified by the literature. Further, banks which were most closely related to each other in one of the networks, were often not part of the same community in other types of network. The individual ties formed between banks are correlated between networks, but the communities created by clusters of close associates are frequently different. These communities suggest there was not a general social capital or prominence throughout the network that led to client sharing. There is no singular elite group. Instead, specific personal ties led to a complex mesh of overlapping interests.

7 Discussion

So, what exactly do these results represent? There seems to be evidence of relationship banking, just not in its purest form. Merchant banks produced private information, which

Figure 6: Network dendrogram, using edge betweenness clustering

Note: Network community dendrograms plotted using edge betweenness algorithm. For an explanation see the accompanying text.
Sources: Various, see Data section.

enabled drawers to access capital from a wide range of sources. However, information about them was frequently not proprietary, the relationship between merchant banks and drawers was not singular. Instead, drawers engaged with a number of different merchant banks, with personal ties to each other. This likely reduced, but did not remove, the incentives of merchant banks to produce information about drawers. They were not willing to fully guarantee some prospective clients, and in these instances sometimes relied on information from collaborating banks. This suggests the system was less competitive, less efficient than a purer model of relationship banking.

The variety of relations between merchant banks and drawers is crucial to our understanding of the global structure of the money market. It suggests that the degree to which relationship banking operated depended on the specialisation of the guaranteeing bank. Where this specialisation was less pertinent, it depended on relations within the merchant banking community. This seems to complement recent evidence about the operation of Kleinworts (Accominotti et al., forthcoming). The size of their clients varied drastically, but not randomly. In areas where they were less geographically specialised, like the US and East Asia, Kleinworts seem to have engaged with larger, institutional clients; for instance, banks and trading houses. Whereas in Germany, the area of their specialisation, clients were mostly small merchant firms, located in remote towns. Diseconomies of scale and the relatively small size of each merchant bank meant they were not able to engage equally with all merchant communities around the globe. Client sharing likely involved more of the larger, institutional drawers, about whom more public information was available. The availability of this information would reduce the cost of sharing private information about these firms. Conversely, merchant banks had greater incentives to retain for themselves smaller clients operating in areas where they had an informational advantage. This has important implications for the ease with which smaller firms overseas could access capital. It depended on whether that particular community was represented among London bankers. It is likely that firms without this benefit had to be large and reputable enough to gain the trust of several different merchant banks. As with underwriting, co-operation seems to have emerged where informational costs were high. Even the great rivals Rothschilds and Barings, entered loan syndication agreements together (Ferguson, 2000, p. 760). When engaging with trade finance on a larger scale, similar forms of co-operation seem like a natural outcome.

Nonetheless, for this co-operation to emerge, there must be plausible mechanisms through which it operated. The argument is not that personal relations necessarily caused client sharing, but that client sharing emerged from the structure of the market. It was the choice of who to share these clients with that related to personal ties, but sharing arose from the desire to distribute risk better. There is a long sociological literature about the relationship between trust and shared-group membership. A large component of this is the expectation of reciprocity (Foddy et al., 2009). This could greatly reduce the barriers that might normally stand in the way of client-sharing.

There is certainly scope for more work on the mechanisms, but I give a few different possibilities below. The simplest, and most likely, explanation is that the extent of information-sharing was relatively minimal. Merchant bankers who were more closely connected were more likely to be aware of each other's clients. At the very least, this could reduce search costs and, depending on the depth of the information, reduce the amount of investigation required. This is a weaker version of the idea that they directly and intentionally shared financially relevant information with each other. There is not much evidence in the literature that banks traded informational reports about clients outside of organising specific deals. What is needed is more work on the agents of these banks overseas. The extent to which banks used the same agents or these agents engaged with each other are likely crucial determinants of client sharing. Where details of these agent are known, it seems that they sometimes existed in expat communities of London merchants. This was certainly the case with Barings' agent in Argentina, Nicholas Bouwer (Vedoveli, 2018).

A more general way of framing this is by thinking about the relation between personal connections and information production. There is limited empirical work on the subject, but there is some evidence that in financial markets information production can be crowded out by social connections. A paper by Han and Yang (2013) has shown this effect at play. In a randomised, experimental set-up they examined the extent to which social communication crowded out information production. Participants were asked to make trading decisions and invest in information production regarding a risky asset of unknown quality. Where agents were allowed to communicate with other agents, they invested significantly less in learning about the asset. If this effect is at play here, then it would suggest significantly less information was produced by the merchant banks.

8 Conclusion

This paper introduces new data on the lives of merchant bankers to show that client-sharing between their banks was related to personal networks. Re-examining the data on acceptances, particularly those of merchant banks, it shows a more qualified form of relationship banking at play. Merchant banks seem to have engaged in longstanding relations with clients, and to have reduced information asymmetries. However, most drawers had relations with multiple merchant banks. This indicates reduced incentives for information production compared to a pure relationship banking model. Where client sharing occurred, it was related to personal ties between merchant banks. Drawers who were linked to multiple merchant banks would connect to those which shared personal links with each other. Collaboration between merchant banks would reduce information costs for assessing borrowers who were already linked to a merchant bank. This would give merchant banks fewer reasons to seek out novel borrowers. While this probably did not affect borrowers in areas where merchant banks had particularly strong specialisations, newer borrowers elsewhere may have struggled to access the London money market. This could lead to greater market concentration, particularly in areas with few personal connections to merchant bankers in London.

Overall, the proportion of shared drawers was reasonably high for merchant banks, at 52.9 percent. Client sharing was not limited to specific types of merchant bank. There was no non-competitive aristocratic core, and dynamic periphery. Instead, the practice seems to permeate merchant banking more broadly. This suggests it may have been an intrinsic feature of the business model of these banks, perhaps related to the scaleability of soft-information production. However, within the merchant banks, the extent of client sharing does not seem closely related to size. Perhaps once merchants reached this more institutional scale, where they acted as acceptors for transactions unrelated to their trading activities, they began to shift away from a model based purely on relationships with borrowers.

Among the merchant banks, sharing personal ties is closely related to sharing drawers. This is tested using two different sets of simulations. These show that the relationship between personal ties and client sharing were not simply the result of overlap in different forms of prestige. If this were the case, then simulations where the prestige or popularity of each bank is held constant should give similar results. They does not. The relation between personal ties and client-sharing is particularly strong when looking at co-directorship of non-merchant banks. This could be because directorships represented a tighter personal bond than club memberships and were related to shared interests within the banking sector. The effect is strong, with a small number of personal connections relating to a substantial increase in the number of shared clients. Overall, these findings suggest that shared clients were the result of collaboration. Client sharing related closely to personal proximity between banks. The exact mechanisms for client sharing remain unclear and there is ample scope for further research on this question.

References

Accominotti, O., Lucena-Piquero, D., and Ugolini, S. (2021). The origination and distribution of money market instruments: sterling bills of exchange during the first globalization. *The Economic History Review*, 0(0):1–30.

Accominotti, O., Noble, A., and Ugolini, S. (forthcoming). British banks and the production of safe assets, 1875-1914.

Accominotti, O. and Ugolini, S. (2019). International trade finance from the origins to the present: market structures, regulation, and governance. *CEPR Discussion Paper No. DP13661.*

Bassett, H. H. (1901). *Men of note in finance and commerce, with which is incoporated men of office. A biographical business directory.* Effingham Wilson.

Boot, A. W. (2000). Relationship banking: What do we know? *Journal of Financial Intermediation*, 9(1):7–25.

Boot, A. W. and Thakor, A. V. (2000). Can relationship banking survive competition? *The Journal of Finance*, 55(2):679–713.

Cassis, Y. (1984/1994). *City bankers, 1890-1914.* Cambridge University Press.

Cassis, Y. (1985). Bankers in english society in the late nineteenth century. *Economic History Review*, 38(2):210–229.

Cassis, Y. (1988). Merchant bankers and city aristocracy. *British Journal of Sociology*, 39(1):114–120.

Cassis, Y. (2010). *Capitals of capital: the rise and fall of international financial centres 1780-2009.* Cambridge University Press.

Chapman, S. D. (1986). Aristocracy and meritocracy in merchant banking. *The British Journal of Sociology*, 37(2):180–193.

Chapman, S. D. (2005). *The rise of merchant banking.* Taylor & Francis.

Daunton, M. J. (1988). Inheritance and succession in the city of london in the nineteenth century. *Business History*, 30(3):269–286.

Diaper, S. (1983). *The history of Kleinwort, Sons & Co. in merchant banking, 1855-1961.* PhD thesis, University of Nottingham.

Ellis, A. (1960). *Heir of Adventure: The story of Brown, Shipley & Co., Merchant Banks 1810-1960.* Burrup, Mathieson & Co., Ltd.

Farinha, L. A. and Santos, J. A. (2002). Switching from single to multiple bank lending relationships: Determinants and implications. *Journal of Financial Intermediation*, 11(2):124–151.

Ferguson, N. (2000). *The House of Rothschild: The World's Banker: 1849-1999*, volume 2. Penguin.

Foddy, M., Platow, M. J., and Yamagishi, T. (2009). Group-based trust in strangers: The role of stereotypes and expectations. *Psychological Science*, 20(4):419–422.

Freixas, X. (2005). Deconstructing relationship banking. *investigaciones económicas*, 29(1):3–31.

Gillett Brothers Discount Company (1952). *The bill on London, or, the finance of trade by bills of exchange.* Chapman & Hall.

Gorton, G. (2012). *Misunderstanding financial crises: Why we don't see them coming.* Oxford University Press.

Granovetter, M. (1973). The strength of weak ties. *American journal of sociology*, 78(3):1360–1380.

Granovetter, M. (2017). *Society and economy.* Harvard University Press.

Han, B. and Yang, L. (2013). Social networks, information acquisition, and asset prices. *Management Science*, 59(6):1444–1457.

Jackson, M. O. (2019). *The Human Network: How We're Connected and Why It Matters.* Atlantic Books.

Jansson, T. W. K. (2018). *The Finance-Growth Nexus in Britain, 1850-1913.* PhD thesis, University of Cambridge.

Journal of the Institute of Bankers (1904). *Journal of the Institute of Bankers.*

King, W. T. C. (1936). *History of the London Discount Market.* Routledge.

Kynaston, D. (1996). *The City Of London: Golden Years 1890-1914.* Pimlico.

Lisle-Williams, M. (1984a). Beyond the market: The survival of family capitalism in the english merchant banks. *British Journal of Sociology*, 35(2):241–271.

Lisle-Williams, M. (1984b). Merchant banking dynasties in the english class structure: ownership, solidarity and kinship in the city of london, 1850-1960. *British Journal of Sociology*, 35(3):333–362.

Newman, M. (2010). *Networks: An Introduction.* Oxford University Press.

Noble, A. (forthcoming). Friends in High Places? Victorian Social Clubs and the 'Gentlemanly Capitalist' Elite (1861-1911).

Petersen, M. A. and Rajan, R. G. (1994). The benefits of lending relationships: Evidence from small business data. *The Journal of Finance*, 49(1):3–37.

Sharpe, S. A. (1990). Asymmetric information, bank lending, and implicit contracts: A stylized model of customer relationships. *The journal of finance*, 45(4):1069–1087.

Vedoveli, P. (2018). Information brokers and the making of the baring crisis, 1857–1890. *Financial History Review*, 25(3):357–386.

Wake, J. (1997). *Kleinwort, Benson: The History of Two Families in Banking.* Oxford University Press, USA.

Ziegler, P. (1988). *The sixth great power: Barings 1762-1929.* HarperCollins.

Appendix

A Network Notation

Networks can be represented mathematically by a set of nodes connected by edges. A one-mode network, such as that between the banks, can be represented by a 2-tuple (V,E), where V is the set of nodes and $E \subseteq V \times V$ is the set of edges. The network can be encoded as an $n \times n$ matrix $\mathbf{Y}$, where n is the number of nodes (banks) in the network. Y_{ij} equals 0 if there is no edge between i and j, or equals 1 if there is a single edge between i and j. If there are multiple edges between i and j, then Y_{ij} is the number of those edges. For instance, if there are 3 edges between i and j, then $Y_{ij} = 3$. These multiple edges are therefore considered as a single weighted edge wherever $Y_{ij} > 0$. The number of these weighted edges in a network is denoted m.

B Clustering Measures

Formally, the clustering coefficient (or transitivity) C can measured as:

$$C = \frac{(\text{number of triangles}) \times 3}{\text{number of connected triples}} \tag{1}$$

,

where a triangle is any three nodes ijk with edges $(i,\ j)$, $(j,\ k)$ and $(k,\ i)$ and a connected triple is any three nodes ijk, with edges $(i,\ j)$, $(j,\ k)$ (and edge $(k,\ i)$ can be present or not).

C Centrality Measures

Here I give definitions various centrality measures for one-mode networks. These are taken from Newman (2010).

- Degree centrality is defined as:

$$D_i = \sum_{j=1}^{n} Y_{ij} \tag{2}$$

- Closeness centrality is defined as:

$$C_i = \frac{1}{n}\sum_j d_{ij}, \tag{3}$$

where d_{ij} is the distance of the shortest path between i, j. The path length between two *connected* nodes is the inverse of the weight of the edge between them, i.e. $length_{i,j} = \frac{1}{Y_{ij}}$, where i, j share a direct edge with each other.
- Betweenness centrality is defined as:

$$B_i = \sum_{st} n^i_{st}, \tag{4}$$

where s, t are any pair of nodes in the network, and n^i_{st} equals 1 if the shortest path between those nodes runs through i, 0 otherwise. The path length between two *connected* nodes is the inverse of the weight of the edge between them, i.e. $length_{i,j} = \frac{1}{Y_{ij}}$, where i, j share a direct edge with each other.
- Eigenvector centrality is defined as:

$$E_i = \sum_j Y_{ij}E_j, \tag{5}$$

where Y_{ij} is an element of the adjacency matrix, i.e. a connection between nodes, and E_j is the eigenvector centrality of each node j. Thus, it is the sum of the eigenvector centralities of connected nodes.

D Network Simulations

The networks are simulated according to $G(n, m)$ type models (for more details see Newman (2010)). In this model the number of nodes n is kept constant. Here n represents the number of merchant banks, 72. The number of edges in the simulated networks are kept constant, though these vary for each of the four types of network (i.e. Bills Shared, Bank Memberships, Business Memberships, and Club Memberships). For each set of simulations I generate 1,000 networks of each type. The same set of simulated networks are used for both the clustering and matrix correlation results.

In Simulation 1 the m edges are distributed randomly between pairs of nodes (i, j). To avoid multiple edges between the same pairs of vertices, pairs are sampled randomly from a list of all possible pairs, without replacement. This is done m times. Weights for these edges are taken from the adjacency matrix $\mathbf{Y}$ and randomly assigned to an edge on a one-to-one basis. Effectively we select 1,000 graphs at random from the collection of graphs G, with a uniform probability distribution $P(G) = \frac{1}{\omega}$ for all graphs with n nodes and m edges, were ω is the number of such graphs.[10]

In Simulation 2 the degree (number of connections of each node) is kept constant. This is done by pairing each half-edge coming from a node i with a half-edge coming from a node j. The procedure simply goes through the list of edges, and breaks each into two separate half-edges connected to two nodes i, j. The simulation then randomly samples pairs of half-edges without replacement, and connects these together. This is repeated until there are no half-edges left to be sampled. Each half-edge is given half

[10]Not including complex graphs with multiple edges between the same nodes or self-edges.

the weight which that edge had in the observed network. That is, the half edge taken from Y_{ij} for Y_i is given the weight $\frac{Y_{ij}}{2}$. This means the half-weight on half-edges is kept constant, which helps preserve the strength with which each node is connected to other nodes. Basically, for each edge half of the weight is randomly determined and half is fixed. Overall, each node has a constant number of connections, and a similar weight. However, which other nodes they connect to is random. Here, we are just sampling from the collection of random graphs G, with n nodes, m edges, the same unweighted degree sequence as the observed graph, and a semi-randomised weighted degree sequence.

E Simulation Diagnostics

Table 6: Simulated network diagnostics

Type	N	Degree	Closeness	Betweenness	Eigenvector
Shared Bills					
Observed	1	6.94	0.00	17.22	0.11
Simulation 1	1000	6.94	0.02	119.34	0.12
		(0.00)	(0.00)	(6.19)	(0.04)
Simulation 2	1000	6.94	0.02	119.25	0.12
		(0.00)	(0.00)	(6.87)	(0.04)
Bank Memberships					
Observed	1	1.47	0.00	0.39	0.17
Simulation 1	1000	1.47	0.00	52.59	0.05
		(0.00)	(0.00)	(24.09)	(0.04)
Simulation 2	1000	1.47	0.00	52.54	0.05
		(0.00)	(0.00)	(24.13)	(0.04)
Business Memberships					
Observed	1	7.00	0.00	14.91	0.16
Simulation 1	1000	7.00	0.01	69.91	0.31
		(0.00)	(0.00)	(1.90)	(0.06)
Simulation 2	1000	7.00	0.01	69.86	0.31
		(0.00)	(0.00)	(2.54)	(0.06)
Club Memberships					
Observed	1	5.00	0.00	13.19	0.13
Simulation 1	1000	5.00	0.01	84.37	0.09
		(0.00)	(0.00)	(3.50)	(0.02)
Simulation 2	1000	5.00	0.01	84.30	0.09
		(0.00)	(0.00)	(4.15)	(0.02)

Note: This table compares structural characteristics of the simulated networks with the observed networks. I use the weighted versions of these measures, with edge weight used as distances for the closeness and betweenness centrality calculations. The figures in brackets are standard errors of G or Y, rather than within a particular network. The same simulated networks are used for both the clustering and inter-network edge correlations.
Sources: Various, see Data section.

F Probability Density Graphs

This section provides the results from Table 5 as kernel density plots. For brevity, only results from Simulation 2 are included here. As these results are less strongly significant than the results from Simulation 1.

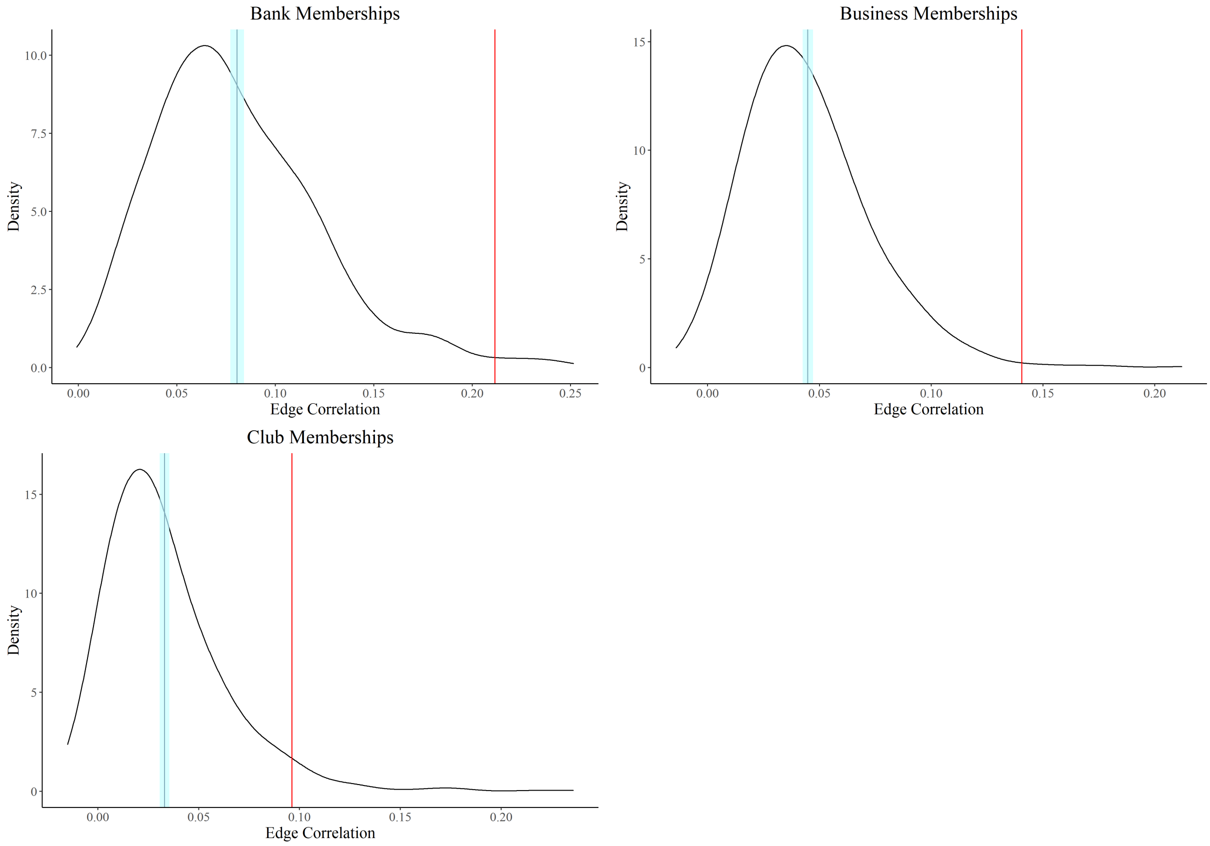


Figure 7: Density plot, observed vs simulated inter-network correlations

Note: The density plot shows the distribution of the correlations between 1000 simulated networks of the given type (i.e. Bank Memberships, Business Memberships, and Club Memberships) and 1000 simulated Bill Sharing networks. This figures shows the results from Simulation 2, see Appendix D. The black vertical line is the mean value of the simulations, while the red vertical line is the observed value. The shaded region represents 99 percent confidence intervals. Bandwidth = 0.01
Sources: Various, see Data section.