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Banks' interconnections and peer effects: Evidence from Chile

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ABSTRACT

In this paper, we identify and quantify the importance of endogenous peer effects in the interbank market, allowing for varying degrees of intensity of these peer effects. We base our analysis on a unique dataset that includes all interbank loans that have taken place between 15 banks in the Chilean interbank market representing more than 95% of the market between 2009 and 2016. This approach contrasts sharply with the geographical definition of peers used by most of the literature. As an application of our model, we examine an episode of liquidity shortage experienced by one Chilean bank in the interbank market, with the lenses of our model. We show evidence consistent with a herding behavior of the lender banks which, according to our model, were peers of the stressed bank.

1. Introduction

Motivated by concerns over herding and financial market instability, the study of financial interconnections and the role of peers in financial decisions have received increasing attention in recent years (Uchida and Nakagawa (2007), Foucault and Fresard (2014), Blasques et al. (2018), Bonfim and Kim (2019), Silva (2019), among others). Indeed, since the 2007–2009 global financial crisis, the discourse about bank safety has widened from viewing the riskiness of financial institutions as individual firms to also understanding and quantifying the degree to which institutions are financially interconnected (Jackson et al., 2017). Within this agenda, studying interbank assets and liabilities is important as they show actual risk exposures between banks. On top of this, peer effects add an additional layer to the analysis by capturing the amplifying effects that may arise from changes in those interbank connections through peer effects. In effect, measuring the extent at which financial institutions' decisions are related to each other provides a critical step forward in assessing risks in the system as a whole. The objective of this paper is to propose a flexible approach to quantify this additional layer of amplifying effects. We do this by identifying and measuring the importance of peers in the interbank market relying on data on interbank cross-exposures.

In this study, a peer effect means the possibility that the lending/borrowing choice of two given banks in the interbank market (one bank being the lender and the other, being the borrower) are affected, in an economically significant way, by the lending/borrowing decisions of another pair of banks. Our definition of peer effects covers an ample set of possibilities. To illustrate some of them, consider four banks, namely banks D, E, F and G. Let us assume that bank D lends to bank F and bank E lends to bank G. A possible peer effect is that bank E's lending to bank G follows bank D's decision of lending to bank F because, for example, F and G have a similar risk profile. A less subtle peer effect would be that, instead of lending to bank G, bank E starts lending to bank F following the observed action of

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bank D. We can think of a particular case of the more general ones previously described, where F and G are the same bank. We call the latter a 'common borrower' interbank connection. Provided that bank D influences E's action, both situations may be forms of herd behavior, which can have important adverse systemic consequences (Scharfstein and Stein, 1990). Intuitively, to determine there is a peer effect, we require that the correlation of two given bilateral interbank positions is sufficiently strong in a statistical sense. Notice that the correlation of banks' choices in the interbank market may arise either from the lenders, as previously described, but also from the borrowers, if they can make an active decision about who to borrow from and they are influenced by peers in their decisions. For instance, bank F borrows from D and bank G borrows from E following F. Since our approach examines correlations in either case, the distinction of whether it is the lender or the borrower bank who follows each other is not relevant for the purposes of our work.

Continuing with the illustrations, another example would be that of a 'common lender', where bank D and E are the same bank. Suppose a negative shock to bank F that increases its risk. In our framework, the increase in bank F's risk may then have an impact on the amount bank D (=E) lends to G, even if nothing has changed in the latter's balance sheet. The impact of this situation on the system can be further amplified if the lending of other banks is correlated to that of bank D to F or G. These relations are hence critical to unveil systemic risk and our approach can identify them. Notice that peers in this case can arise because, say, bank G follows F in tapping a certain source of funds, or because bank D's decisions concerning banks F and G are correlated. An important additional example would be when banks D and G are the same bank, let us call it bank D; and E and F are also a single bank, let us call it bank F. We call this interbank connection a case of 'reciprocity'. More generally, properly identifying peer effects is important because these effects imply that banks may move in tandem, which can act as an amplifier (or absorber) of shocks affecting specific institutions and/or market prices.

Our case of application is the Chilean interbank market. The dataset is unique as it includes all interbank loans between 15 banks representing more than 95% of the Chilean interbank market. The main finding of our paper is that we show evidence of peer peer effects in the interbank market, with two types of peer effects being the dominant ones, that is, the common lender and the reciprocal interactions. We then apply our model estimates to examine an episode of liquidity shortage experienced by one bank in the interbank market. Interestingly, we show robust evidence consistent with a herding behaviour of some lender banks to the bank experiencing the liquidity shortage, where possibly the signal of some of them reducing the amount lent to the stressed bank may have made other peer lender banks to follow suit.

The reasons for peer effects in interbank markets can be various. One possible reason is that a bank may choose to free ride on its peers' market research and follow their lending or borrowing decisions, if those peer banks are perceived as having greater expertise (Bikhchandani et al., 1998; Banerjee, 1992). For example, a lender bank may follow its peer lenders and reduce its exposure to a given borrower in a collective response to (risky) financial decisions of the latter (Caballero and Simsek, 2013). Another possibility is that banks may find optimal to mimic each other and invest in the same type of assets, in the expectation of collective bailouts were things to turn sour (Acharya and Yorulmazer, 2007; Ratnovski, 2009; Farhi and Tirole, 2012). Alternatively, banks may be sensitive to the decisions of their peers, with which they have agreements of reciprocity and/or long-term lending relations (Cocco et al., 2009) with these relations providing them some cross-insurance (Blasques et al., 2018).

While economically relevant, identifying the causal effect of peers is empirically challenging (Manski, 1993).[1] Acknowledging these challenges, we rely on the identification results of Bramoullé et al. (2009) and De Giorgi et al. (2010), who show, independently, that there is identification if units belong to different, not fully overlapping groups. In our study, the definition of unit of analysis crucially enables identification: Our unit of analysis is the lending/borrowing position between any two banks in the interbank market. Therefore, the peer groups in our framework are specific to each bilateral interbank position: Peer groups are searched for among other bilateral interbank positions (and not among banks). This implies that the numbers of possible elements belonging to a given peer group is rather large (which equals $n \times (n-1)$, with $n = 15$ being the number of banks in our data) and that the possibility of overlapping among groups is very low. Empirically, the peer groups that we identify are of different sizes and do not overlap; hence, the condition for identification is fulfilled. On top of that, because we find evidence of strong cross-sectional dependence in our dataset, we model these unobserved common factors by means of factor models.[2]

To characterize the way(s) banks interact in the interbank market, we start by estimating an interbank connection matrix: Each entry in this connection matrix corresponds to a pair of bilateral interbank positions. We say that two bilateral interbank positions are significantly connected, and are peers of each other, if the sample estimate of the correlation of the two positions over the time frame is statistically different from zero; otherwise, they are unconnected. To identify the causal effect of peers, we then treat the estimated

[1] One key challenge is to determine what drives the correlation between outcomes of units of analysis, in our case, banks' choices in the interbank market. In a pioneer study, Manski (1993) distinguishes between contextual effects (which in this paper refers to the influence of exogenous characteristics that both a given interbank position and the others in the peer group share), endogenous effects (namely, how banks' lending/borrowing choices in the interbank market are affected by the behavior of their peers) and correlated effects (all banks in the same local network are subject to unobserved common shocks that lead them to take similar decisions). Manski (1993) shows that there are two main identification problems. First, due to simultaneity in the behavior of interacting agents, he shows that peer effects cannot be identified in a linear-in-means problem with various groups but where a given individual belongs to one group only (the reflection problem). Second, he shows that it is difficult to distinguish real (endogenous or contextual) peer effects from correlated effects.

[2] Regarding the separation between the endogenous and the contextual peer effects, we conduct a Bayesian model comparison test (Hepple, 2004; LeSage, 2014) which favors excluding the contextual effects from the analysis. This is reasonable, given our unit of analysis. Therefore, we conclude that controlling for the lender and borrower banks' characteristics (as we do), as well as the common factors, is sufficient to determine the causal effect of peers in the interbank market. Other papers that assume no contextual effects are Norton et al. (1998), Trogdon et al. (2008), Gaviria and Raphael (2001), Powell et al. (2005).

interbank connection matrix as a weight matrix and estimate a heterogenous spatial autoregressive model or HSAR model (Bailey et al., 2016a). More precisely, the model relates the bilateral interbank positions with (lagged) lender- and borrower-specific balance sheet characteristics, as well as heterogeneous spatial autoregressive parameters (one estimated parameter for each bilateral interbank position), measuring the strength of peer effects in banks' choices in the interbank market. The estimation method is a quasi-maximum likelihood procedure, which accounts for the endogeneity of the interbank connection matrix.

We combine information from two datasets. On the one hand, we have access to a regulatory dataset, containing the monthly evolution of total bilateral positions in the Chilean interbank market, over the period January 2009 to March 2016. On the other hand, we observe banks' balance sheet characteristics, at a monthly frequency. Our set of 15 banks include both domestic and foreign banks. Our dataset is unique in that it includes all interbank loans between these 15 banks, and contains information on the loan's date, amount and identity of the lender and the borrower. Having this detailed information over a long period of time is a major feature of our paper, whereas the network literature typically approximates individual exposures from aggregates through algorithms.

Chile offers an interesting case of study, since it is an emerging economy, which has experienced a recent rapid growth in its income and a considerable development of its financial market in the recent past. To provide some figures, in 2014, banks' assets in Chile represented 122% of GDP, above the 94% mean share that banks' assets represented within a sample of 20 emerging economies over the same period. Also, the Chilean financial market has a level of concentration similar to that of many systems in the world (the four largest banks represent 64% of the system), and there is a mix of foreign and domestically owned banks. Furthermore, the size of the Chilean interbank market (7.3% of the Chilean financial assets, as of 2015) is comparable to the size it represents in the rest of the world (6.8% relying on a sample of 225 banks all over the world, for the same period).

From the estimation of the interbank connection matrix, we find 60 statistically significant interbank connections. Two types dominate, namely, the reciprocal and the common lender connections. As previously presented, a reciprocal interaction occurs when the pair of bilateral interbank positions that are significantly connected involves only two distinct banks. Therefore, in the above example, the positions that correlate are the lending of bank D to F, and its reciprocal, namely, that of bank F to D. In turn, there is a common lender interaction when the pair of bilateral interbank positions being significantly connected involve a unique lender bank. Interestingly, we find that the reciprocal and the common lender interactions account for more than 90% of the significant interbank connections we identify.

Regarding the banks present in the reciprocal and common lender interactions, results show that treasury banks (that is, banks which are mostly subsidiaries of foreign banks, whose core activity is to provide investment banking services), have the largest number of reciprocal interactions and interestingly, in the bilateral interbank positions which we classify as being part of the reciprocal connection type, they tend to lend to and borrow from a smaller number of counterparties. This finding is consistent with these banks being sensitive to the lending/borrowing choices of the banks with which they have long-term relations, with these relations possibly being some form of cross-insurance between them. In addition, we observe that almost all lender banks in the common lender interactions are medium-sized commercial banks and that these banks make significantly more money when lending to the banks with which they are significantly connected to, relative to the average returns they obtain when lending to other banks. The way we read this finding is that lenders in the common lender interactions provide a stable source of funding to the borrower banks involved, thus enabling these lenders to charge higher interest rates in exchange. Consistent with that interpretation, we show that the amounts traded in the distinct bilateral interbank positions being part of the common lender interactions are less dispersed (over the sample period) than the amounts traded in the remaining bilateral positions involving the same lender banks.

Looking at the bank characteristics which make banks more likely to have interbank positions which are sensitive to their peers (other interbank positions), we find that size and business focus are the most salient features and that small and treasury borrower banks are the most sensitive ones. Knowing that treasury banks are small, one possible way to interpret the latter is that small banks are more sensitive, because they are more exposed to the risk of not getting funding from other banks in the interbank market. Interestingly, small banks also appear to have less credit risk and more capital, relative to big banks. Being well capitalized and having a low exposure to credit risk may be complementary ways to insure against liquidity risk and to increase their probability of survival in the event of a crisis.

Finally, concerning the application, we consider an episode of liquidity shortage experienced by one Chilean bank, let us call it bank A, which took place in the first half of 2010s. The exercise consists of using the HSAR estimates to predict which banks react more to the liquidity crisis of bank A and contrast this with what happened in reality. Specifically, we form two groups of all bilateral interbank positions involving bank A as the borrower and the 14 remaining banks as lenders: One group includes bilateral interbank positions (between the 14 lender banks and bank A as borrower) exhibiting non-zero HSAR parameter estimates. In the other group, there are those bilateral interbank positions having bank A as the borrower but with zero HSAR parameter estimates. The main finding of the application is that while before the crisis, the level and pattern of the total amount lent to bank A was similar between the two groups, during and after the crisis, lenders in the interbank positions (having bank A as the borrower and) with non-zero HSAR parameter estimates lent remarkably less to bank A, relative to the uncorrelated group (and relative to the period before the crisis). It thus provides evidence consistent with herding, where possibly the signal(s) of one of the (some) lenders reducing its (their) lending to the bank experiencing the liquidity shortage made other lender banks to follow suit and also reduce their funding to A.

Wrapping up, this paper proposes a framework that identifies peers statistically and offers the necessary flexibility to allow for different degrees of intensity of the peer effects and for various types of interbank connections. By applying it to the Chilean interbank market, we identify which types of banks are more sensitive to the lending/borrowing decisions of their peers; we then illustrate how our approach could be applied to simulate the possible impact in the interbank market of a crisis of a given bank. The latter should be of interest for policy makers with a mandate on financial stability, as well as researchers.

The remainder of the paper is organized as follows. Section 2 describes the data and the methodology we use to identify and quantify the importance of endogenous peer effects. Section 3, in turn, exhibits the empirical results and discusses the main findings of the paper. Finally, Section 4 concludes. The appendix contains additional descriptive statistics, details of the methodology and results, absent in the main text.

1.1. Related literature

This paper is linked to the growing literature showing that peers have a significant role on banks' decision-making. Empirical evidence shows that peers can affect banks' funding liquidity policies (Bonfim and Kim, 2019; Silva, 2019), banks' credit policies (Uchida and Nakagawa, 2007), banks' risk management policies (Liedorp et al., 2010; Craig et al., 2014; Tonzer, 2015), group lending (Li et al., 2013), trading decisions (Ng and Wu, 2010), online lending markets (Iyer et al., 2016), among other domains. Typically, the identification of peers is geographic.

Specific to the study of peer effects in interbank markets, the literature has shown that the reasons for peer effects can be various. For instance, a bank may choose to free ride on its peers' market research and follow their lending and/or borrowing decisions, if those peer banks are perceived as having greater expertise (Bikhchandani et al., 1998; Banerjee, 1992). Or banks may find optimal to mimic each other and invest in the same type of assets, in the expectation of collective bailouts were things to turn sour (Acharya and Yorulmazer, 2007; Ratnovski, 2009; Farhi and Tirole, 2012). Alternatively, banks may be sensitive to the decisions of their peers, with which they have agreements of reciprocity and/or long-term lending relations (Cocco et al., 2009), with these relations providing them some cross-insurance (Blasques et al., 2018). An additional possibility is that peer effects can be such that a bank (or group of banks) may reduce its (their) exposure to a given bank in response to (risky) financial decisions of the latter (Caballero and Simsek, 2013). A further reason for peer effects may be reputational concerns (Scharfstein and Stein, 1990).[3]

We share with this literature the conclusion that peer effects matter in explaining banks' lending/ borrowing choices in the interbank market. Precisely, we provide evidence consistent with the hypothesis of banks being sensitive to the decisions of their peers with which they have agreements of reciprocity and/or long-term lending relations, and that some of the peer effects we identify are asymmetric, in the sense that several lenders appear to be sensitive to the decisions of their peers, but few borrowers. Furthermore, in the application, we show evidence consistent with herding, with the group of correlated lender banks to the bank under stress considerably reducing their lending to the stressed bank following the liquidity shortage. We contribute to this literature in two dimensions. On one hand, because instead of using a geographic or business type definition of peers, we identify peers statistically. Our approach is hence more flexible and general, as it permits potentially to identify peers based on other non-observed characteristics. On the other hand, we add to it by allowing for heterogeneous parameters to measure the intensity of peer effects. This is novel, since literature to date has mainly focused on a single parameter to measure the influence of peers (Liedorp et al., 2010; Craig et al., 2014; Silva, 2019). Allowing for heterogeneous coefficients is important, as we show that not all bilateral interbank positions are related to each other, on the contrary, there is considerable variabiliity between them, with some being very sensitive and others, not at all. Accounting for heterogeneity could also be of interest for policy makers and researchers conducting stress-tests, simulations and financial stability analyses.

The paper closest to ours is to Craig et al. (2014), who estimate a spatial probit model to study whether other banks' choices in the German interbank market affect the probability of distress of a specific bank. We add to this work by accounting for heterogeneity when modelling banks' lending/borrowing choices in the interbank market. Another paper that is close to ours is Leary and Roberts (2014). We share with it that the authors do not rely on geography to identify peers. Leary and Roberts (2014) study corporate financial policy of firms and find that peer effects matter more than traditionally identified determinants. Also, they show that smaller and less successful firms are highly sensitive to their larger, more successful peers, but not vice versa.

2. Data and methodology

Section 2.1 first presents the data and some descriptive statistics; it then characterizes the Chilean interbank market. In turn, Section 2.2 introduces the notation needed to model interbank connectedness and outlines how we apply Bailey et al. (2016a) two-step methodology to obtain, first, an estimate of the interbank connection matrix and second, estimates of the heterogenous spatial autoregressive model. For comparison, we also consider the homogenous spatial autoregressive model. Finally, Section 2.3 discusses the representativeness of our data and the scope of our methodology.

2.1. The data

The time frame goes from January 2009 to March 2016. We combine information from two datasets, whose source is the banks' supervisor in Chile, the Superintendency of Banks and Financial Institutions. First, to measure banks' positions in the interbank market, we use a regulatory and supervisory dataset: Chilean banks must report all their exposures (outstanding amounts) to other banks, on a daily basis, by financial instrument. Instruments comprise term deposits, derivatives, outstanding operations (in process of

[3] In this case, peer effects overlap with the concept of herd behavior, which is a possible consequence of peer effects. Reputational concerns as a source of peer effects leading to herd behavior go as far back as Keynes's General Theory. In Keynes's words: "Worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally". Building on these intuitions, Scharfstein and Stein (1990) develop a model of herd behavior.

being liquidated), bank bonds, overnight loans without collateral, current accounts, repurchase agreements and overnight loans with collateral. We add them up and then compute the mean, by month, of the total bilateral interbank positions between any lender and any borrower bank in the interbank market; they are hence, stocks. This will be our dependent variable.

We consider a set of 15 domestic and foreign banks, with the latter being subsidiaries of the foreign entities. These 15 banks actively participate in the interbank market over the period, and they are representative of the Chilean interbank market.[4] Fig. A1, in the appendix, supports this idea by showing that the interbank assets and liabilities of our 15 banks represent 96% and 98% of the total interbank assets and liabilities, respectively, with these proportions having been stable over the period under study. The sample thus comprises 18,270 observations (15 banks over 87 periods, i.e. $15 \times 14 \times 87$). Our dataset is unique in that it includes all interbank loans and contains information on the loan's date, amount and identity of the lender and the borrower. Having this detailed information over a long period of time is a major breakthrough, relative to the empirical literature on interbank markets, which typically has to approximate individual exposures from aggregates through algorithms.

The second dataset provides monthly information on the banks' balance sheet characteristics; specifically, we consider variables related to banks' risk and performance, access to alternative sources of funding and scale covariates. Specifically, to proxy for banks' risk and performance, we include the proportion of non-performing loans, defined as loans that are past due for a period exceeding 90 days over the total outstanding credit granted by the bank; the monthly return on assets; and the capital adequacy ratio, which is the ratio of a bank's capital to its risk-weighted assets. A higher capital adequacy ratio thus indicates a less risky bank.[5] To account for the availability of other sources of funding, we consider the stock of foreign liabilities and the stock of total deposits, with the latter including deposits from institutional investors, firms and retail depositors. While banks have certainly other forms of funding (for example, bonds), these variables represent types of funding which are close substitutes to interbank funding. Section A.4, in the appendix, discusses the expected signs of the bank-specific covariates.

Given that the dependent variable is the interbank position between a lender and a borrower bank at a certain point in time, there is not a natural candidate to scale it. In fact, the evolution of the dependent variable would be different if we were to scale it with a lender or a borrower characteristic. One way to deal with this issue is to keep the dependent variable in level and include scale variables for both the lender and the borrower as right-hand side variables in the regressions. The scale variable we choose is total loans, which is the addition of mortgage, commercial and consumer loans.

For robustness, we also add the information on banks' assets; type of property, namely, whether the bank is public (owned by the state, which is the case of only one bank in the country) or private; as well as banks' nationality, that is, whether it is a domestic or a foreign bank. We define a foreign bank as a bank, which has more than 50% of foreign capital. Their inclusion, through dummy variables if at least one bank in the bilateral interbank position is public or foreign, is to examine whether proprietary and nationality heterogeneity matters to explain the extent to which banks participate in the interbank market.

On top of that, as an additional check, we consider the 90-day interest rate that each bank pays in the wholesale market. This is relevant because if banks were to face a higher interest rate in the interbank market than in the wholesale market, they would prefer to lend in (rise funding from) the latter market. Unfortunately, we do not have this variable for the set of 15 banks in the dataset; therefore, we use it as a robustness check only.

Table 1 describes the variables we consider in this study, whereas Table 2 presents the descriptive statistics of the banks' balance sheet characteristics. Finally, Table A1, in the appendix, reports the correlation matrix of the main variables of interest.

2.1.1. *The Chilean interbank market*

The interbank market is one of the main sources of funding for the Chilean banks. To provide some illustrations, over the period 2009–2015, interbank exposures represented, on average, 7.8% of the system's assets, positioning them as the second source of wholesale funding for banks, behind mutual funds (9.7%) but ahead of pension funds (4.9%) (Carreño and Cifuentes, 2017). Relying on cluster analysis, Jara and Oda (2015) identify four distinct types of banks operating in Chile, namely, big and medium-sized commercial banks, retail and treasury banks. Characterising these four types, Jara and Cabezas (2017) explain that big and medium-sized banks are standard commercial banks that participate in all market segments (corporate, consumer and mortgage credits); among them, there are both domestically owned banks and subsidiaries of foreign banks. Retail banks, in turn, are domestically owned, relatively small and focused on households' finance (consumer and mortgage loans). Also, their international activity is almost negligible. Finally, treasury institutions are also small and mainly subsidiaries of foreign banks, whose core activity is to provide investment banking services (corporate finance business and derivatives); they are active in the interbank market. In addition, treasury banks hold the largest amounts of assets and liabilities overseas, compared to the other bank categories. Considering the set of 15 banks that we focus on in this paper, four of them are big banks, seven of them are medium-sized commercial banks, three of them are treasury banks and the remaining bank is retail. In terms of nationality, eight banks are domestic, while the remaining seven are foreign banks. To complement the latter, Table A2, in the appendix, disaggregates the descriptive statistics of banks' balance sheet characteristics by the previously defined four types of banks. Last, nine out of the 15 banks in our dataset are listed banks.

Fig. A2, in the appendix, displays the distribution of interbank assets and liabilities for each bank in relation to their total assets. To preserve anonymity, in this figure, we group banks into three categories: Large, medium-sized, and treasury-retail banks. The figure

[4] Regarding the foreign owned banks, having subsidiaries is the only way foreign banks are allowed to operate in the Chilean system, since operating through branches is not allowed by law.

[5] Banking regulators require banks have minimum levels of capital adequacy ratio to protect depositors and to make sure that banks have enough cushion to absorb a reasonable amount of losses.

Table 1
Description of the variables.

Variables	Period	Source	Unit	Description
Bilateral interbank position	2009m1–2016m3	SBIF	Millions Chilean Pesos	Bilateral interbank exposure that includes include interbank loans, current accounts, repurchase agreements, derivatives, term deposits, bank bonds, interbank loans with collateral and operations in the course of liquidation.
Non-performing loans	2009m1–2016m3	SBIF	Ratio	Loans where the borrower is 90 days past due overt total loans.
Return on assets	2009m1–2016m3	SBIF	Percentage	Return on assets after tax.
Foreign liabilities	2009m1–2016m3	SBIF	Millions Chilean Pesos	Foreign liabilities.
Bank deposits	2009m1–2016m3	SBIF	Millions Chilean Pesos	Term deposits (owned by individuals, firms and financial institutions).
Total loans	2009m1–2016m3	SBIF	Millions Chilean Pesos	Total loans (commercial, consume and others).
Capital adequacy ratio	2009m1–2016m3	SBIF	Ratio	Ratio of a bank's capital in relation to its risk weighted assets and current liabilities.
Interest rate term deposits	2009m1–2016m3	CBC	Percentage	Bilateral interest rate of outstanding term deposits.
Total assets	2009m1–2016m3	SBIF	Millions Chilean Pesos	Total assets.

Notes: This table describes the main variables we consider in the paper. SBIF stands for Superintendency of Banks and Financial Institutions and CBC stands for Central Bank of Chile.

Table 2
Descriptive statistics.

Variables	Obs.	Mean	Median	Std. Dev.	Max	Min	P_{25}	P_{75}
Bilateral position	18,270	45.00	15.24	94.65	1143	0	4.30	40.30
Non-performing loans	18,270	0.78	0.68	0.62	3.82	0	0.44	1.06
Return on assets	18,270	1.22	1.10	1.00	8.35	− 1.16	0.63	1.57
Foreign liabilities	18,270	436	231	496	2099	0	0	688
Bank deposits	18,270	3240	2060	3094	11,849	0	691	5306
Total loans	18,270	6033	3769	6459	25,325	0	716	9646
Capital adequacy ratio	18,270	23	13	28	240	9.16	12.15	15.45
Int. rate term deposits	16,758	3.78	3.84	1.72	7.70	0.12	3.16	5.22
Total assets	18,270	8246	5033	8528	33,727	108	911	12,898

Notes: This table reports the descriptive statistics of the bilateral interbank positions and banks' balance sheet characteristics. Bilateral interbank exposure (in millions of Chilean Pesos) includes include interbank loans, current accounts, repurchase agreements, derivatives, term deposits, bank bonds, interbank loans with collateral, and operations in the course of liquidation. Non-performing loans are loans where the borrower is 90 days past due overt total loans. Return on assets corresponds to the return on assets before tax. Foreign liabilities correspond to foreign liabilities (millions of Chilean Pesos). Bank deposits correspond to term deposits owned by individuals, firms, and financial institutions (millions of Chilean Pesos). Total loans correspond to commercial, consume, and other loans (millions of Chilean Pesos). Capital adequacy ratio is the ratio of a bank's capital in relation to its risk weighted assets and current liabilities. Interest rate term deposits correspond to the bilateral interest rate of outstanding term deposits. Total assets correspond to the total assets (millions of Chilean Pesos). Obs., Std. Dev., Min and Max stand for observations, standard deviation, minimum and maximum, respectively. Int. stands for interest. P_{25} and P_{75} correspond to the percentile 25 and 75, respectively, of the corresponding empirical distribution. Data from January 2009 to March 2016. Data from Superintendency of Banks and Financial Institutions and Central Bank of Chile.

indicates that while interbank exposures represent, on average, 6% of total assets in the case of large and medium-sized commercial banks, for small banks interbank exposures can reach 40% of their assets. We also find that the relation between assets and liabilities is heterogeneous: Whereas some banks regularly have asymmetric positions in the interbank market (being either net lenders or net borrowers), other banks maintain balanced positions.

2.2. Methodology

2.2.1. Modeling interbank connectedness

At any time period t (with $t = 1, \ldots, T$), let Y_t be an $n \times n$ matrix of bilateral interbank positions, where the n columns represent lender banks (l) 1 to n and the n rows correspond to borrower banks (b) 1 to n:

$$\text{Y}_t = \begin{pmatrix} l_1 \to b_1 & l_2 \to b_1 & \ldots & l_n \to b_1 \\ l_1 \to b_2 & l_2 \to b_2 & \ldots & \ldots \\ & & & l_n \to b_{n-1} \\ & & & l_n \to b_n \end{pmatrix} \tag{1}$$

As in LeSage and Pace (2009), we can create an $N \times 1$ vector of bilateral interbank positions, with $N = n \times (n-1)$, from the matrix (1) in two ways: A lender-centric ordering or a borrower-centric ordering. Denote y_t the $N \times 1$ vector of bilateral interbank positions. A lender-centric ordering requires $\mathrm{y}_t^l = \mathrm{vec}(\mathrm{Y}_t)$, whereas a borrower-centric ordering needs $\mathrm{y}_t^b = \mathrm{vec}(\mathrm{Y}_t^{'})$.

Without loss of generality, hereafter, we focus on the lender-centric ordering, hence $\mathrm{y}_t = \mathrm{y}_t^l$, with the first n rows of y_t corresponding to bilateral positions in the interbank market between lender 1 to all the n borrower banks at period t, while the last n rows of y_t referring to bilateral interbank positions between lender n to all the n borrower banks, also at t. Element $y_{i:j,t}$ denotes the bilateral interbank position from the i-th lender bank to the j-th borrower bank at t, with $i = 1, \ldots, n$ and $j = 1, \ldots, n$.

Let W be the interbank connection matrix, which we define as a square $N \times N$ matrix, where the N columns and N rows represent the pairs of bilateral interbank positions between lenders 1 to n and borrower banks 1 to n (recall that in our case, $N = 15 \times 14 = 210$). More precisely, an element $w_{i:j,k:l}$ of W will take the value of one, $w_{i:j,k:l} = 1$, if there is a connection or interaction between the bilateral interbank position involving lender bank i and borrower bank j and the position between lender bank k and borrower bank l (with $i, j, k, l \in 1, \ldots, n$) and zero otherwise, $w_{i:j,k:l} = 0$. By convention, $w_{i:j,i:j} = 0$.

To determine the interbank connections, we compute the correlation of all pairs of bilateral interbank positions. Let $\widehat{\rho}_{i:j,k:l}$ denote the sample estimates of the pair-wise correlation of any two bilateral interbank positions $i:j$ and $k:l$, over the period $t = 1, \ldots, T$, that is,

$$\widehat{\rho}_{i:j,k:l} = \frac{\sum_{t=1}^{T}\left(y_{i:j,t} - \overline{y}_{i:j}\right)\left(y_{k:l,t} - \overline{y}_{k:l}\right)}{\left[\sum_{t=1}^{T}\left(y_{i:j,t} - \overline{y}_{i:j}\right)^2\right]^{1/2}\left[\sum_{t=1}^{T}\left(y_{k:l,t} - \overline{y}_{k:l}\right)^2\right]^{1/2}} \tag{2}$$

where $\overline{y}_{i:j} = T^{-1}\sum_{t=1}^{T} y_{i:j,t}$.

Following Bailey et al. (2016a), we then identify the non-zero elements of W with those elements of $\widehat{\rho}_{i:j}$ in (2) that are different from zero at a suitable significance level. Therefore, two bilateral interbank positions $i:j$ and $k:l$ are connected and are peers to each other (that is, $\widehat{w}_{i:j,k:l} = 1$) if the pairwise correlation between the two bilateral interbank positions $i:j$ and $k:l$ over the sample period is statistically different from zero; otherwise, they are unconnected ($\widehat{w}_{i:j,k:l} = 0$). Note that the procedure requires that the time dimension be sufficiently large.

There is one technical but important point to comment, which is that before computing the pair-wise correlations $\widehat{\rho}_{i:j,k:l}$, we need to test whether the weak cross-sectional dependence assumption holds in the dataset. This is important, because if we reject the null of weak cross-sectional dependence, we should model the implied strong cross-sectional dependence. One way to do it is by means of a factor model, yielding the de-factored observations, as residuals from ordinary least square regressions of the bilateral interbank positions on some principal components. In such a situation, we should then compute the correlation of the de-factored bilateral interbank positions. Appendix A.3 provides technical details on the procedure we follow for testing the weak cross-sectional dependence assumption, for de-factoring the observations and for determining the significant interbank connections.

Finally, it is important to mention that for estimation of the spatial autoregressive models, we normalize $\widehat{\mathrm{W}}$. The resultant interbank connection matrix $\widehat{\mathrm{W}} = (\widehat{w}_{i:j,k:l})$ is such that $\widehat{w}_{i:j,k:l} > 0$ if the two bilateral interbank positions $i:j$ and $k:l$ are connected according to the statistical procedure previously described or $\widehat{w}_{i:j,k:l} = 0$ otherwise.

2.2.2. Assessing the importance of peer effects, through spatial autoregressive models

In order to assess whether endogenous peer effects play any role when modeling banks' lending and borrowing choices in the interbank market, we rely on spatial autoregressive models. These models relate the bilateral interbank positions to the lenders and borrowers' balance sheet characteristics, as well as spatial autoregressive parameters, measuring the strength to which banks' lending and borrowing choices in the interbank market are connected to each other

Specifically, we consider two variants of the spatial autoregressive model. The first one, the homogenous spatial autoregressive model specification or SAR, assumes a single spatial autoregressive parameter. The second one, the heterogeneous spatial autoregressive model or HSAR, allows for heterogeneous spatial autoregressive parameters, one for each bilateral interbank position.

From an econometric standpoint, the failure to account for spatial dependence, when it exists, may lead to inefficient estimated coefficients and prediction bias, among others. From an economic point of view, not accounting for endogenous peer effects, when they exist, implies neglecting that because banks' lending and borrowing choices in the interbank market are connected, a change in a bank's characteristic can impact not only the lending/borrowing decisions of that bank, but potentially the lending/borrowing choices of other banks in the same market. Endogenous peer effects may thus generate feedback loops and growing financial fragility in the event of a crisis.

At any t, define X_t as the $n \times k$ matrix of explanatory variables, containing k bank-specific balance sheet characteristics. Given the $N \times 1$ vector of bilateral interbank positions, y_t, we need to repeat X_t n times to create an $N \times k$ matrix, that we label $\mathrm{X}_{b,t}$, which contains the characteristics of the borrower banks at period t. Hence, $X_{b,t} = i_n \otimes X_t$, with i_n an $n \times 1$ unit vector and $\otimes$ the Kronecker product. Similarly, we define the $N \times k$ matrix of lender-specific characteristics as $X_{l,t} = X_t \otimes i_n$.[6]

The spatial autoregressive model specification with a single spatial autoregressive parameter then writes:

$$y_t = \alpha i_N + \psi \widehat{W} y_t + X_{l,t-1}\beta_l + X_{b,t-1}\beta_b + \epsilon_t, \quad (3)$$

with αi_N an $N \times 1$ constant parameter vector, ψ the single spatial autoregressive parameter, β_l and β_b $(k \times 1)$ vectors of parameters for the lenders' and borrowers' characteristics, respectively, and ϵ_t, the residuals, such that $\mathrm{var}(\epsilon_t) = \sigma^2_\epsilon$. To avoid any endogeneity bias due to simultaneity, all banks' characteristics are lagged one period. For estimation, we rely on Maximum Likelihood (ML) estimation procedures, based on the technical results in LeSage and Pace (2009).[7]

The assumption of a single variance in the SAR model may be restrictive, specially if the dataset contains a large number of bilateral interbank positions. In addition, the ML estimation procedure assumes that the spatial weight matrix is exogenous. These elements constitute the first reason why we prefer the heterogeneous spatial autoregressive or HSAR model specification, which addresses the previous two aspects,

$$y_t = \alpha i_N + \Psi \widehat{W} y_t + B_l X_{l,t-1} + B_b X_{b,t-1} + u_t, \quad (4)$$

with $\boldsymbol{\Psi} = \mathrm{diag}(\boldsymbol{\psi})$, $\boldsymbol{\psi} = (\psi_1, \psi_1, \ldots, \psi_N)'$, $B_l = \mathrm{diag}(\beta'_{1l}, \beta'_{2l}, \ldots, \beta'_{Nl})$, $B_b = \mathrm{diag}(\beta'_{1b}, \beta'_{2b}, \ldots, \beta'_{Nb})$, $\beta_{il} = (\beta_{il_1}, \beta_{il_2}, \ldots, \beta_{il_k})'$, $\beta_{jb} = (\beta_{jb_1}, \beta_{jb_2}, \ldots, \beta_{jb_k})'$ and u_t the $N \times 1$ vector of error terms, such that $u_{ij,t} \sim \mathrm{IIDN}(0, \sigma^2_{u_{ij}})$.[8] For consistent estimation of the parameters, we adapt the Quasi Maximum Likelihood (QML) procedure of Aquaro et al. (2015).[9]

The second reason why we prefer the HSAR over the SAR model relates to the possibilities that the former offers: By exploiting the data in the time dimension, the HSAR model is able to produce estimates for all the bilateral interbank positions. Given previous evidence showing that the interbank network is highly skewed with a few very interconnected core banks and many peripheral banks that trade mainly with core banks (for instance, Blasques et al. (2018)), having heterogenous coefficients becomes appealing, as it allows for different levels of interaction between the bilateral interbank positions. On top of that, examining the significance and magnitude of the heterogeneous spatial parameter estimates can shed some light about the alternative channels of endogenous peer effects (for instance, the expectation, preference and constraint channels according to Manski (2000)).

In spite of the previous reasons, we will still report the model estimates of the SAR, for purposes of comparison, as it provides a first indication of the importance of peer effects. Finally, it is worth mentioning that the higher the spatial autoregressive parameter is, the stronger the connection between banks' lending/borrowing choices in the interbank market should be. This is because a feature of the likelihood-based methods we use is that they ensure that the spatial autoregressive parameter estimates are in the interval defined by the maximum and minimum eigenvalues of the interbank connection matrix (LeSage and Pace, 2009), which in our case equals $(-1, 1)$.

2.3. Discussion on the dataset, methodology and endogeneity issues

To begin with, we focus on the Chilean interbank market, because we have access to a unique data set with all the bilateral interbank exposures, on a daily basis, and for a long period of time. This is a particular feature of the Chilean system that comes from the information requirements set by its regulator. In fact, the empirical literature on interbank markets has struggled developing methods for inferring patterns of bilateral interbank linkages coherent with aggregate exposures (see for example Anand et al. (2018)). Moreover, the specific question we study in this paper could not have been answered with methods that approximate behavior since those approximations would have assigned median or average values, losing precisely the richness of the idiosyncrasies of each bank. It is precisely in these idiosyncrasies where peer effects can be found.

Chile offers an interesting case of study, since it is an emerging economy, which has experienced a recent rapid growth in its income and a considerable development of its financial market in the recent past. To provide some figures, banks' assets in Chile represented 122% of GDP (2014, source HelgiLibrary), above the 94% mean share that banks' assets represented within a sample of 20 emerging economies over the same period, and well above the 66% that they accounted for within 12 Latin American economies. Also, the Chilean financial market has a level of concentration similar to that of many systems in the world (the four largest banks represent 64% of the system), and there is a mix of foreign and locally owned banks.

Furthermore, the size of the Chilean interbank market is comparable to its size in the rest of the world. In this respect, Carreño and Cifuentes (2017) have shown that interbank exposures in Chile represent, on average, 7.3% of the Chilean financial assets (2015), a

[6] At any t, $X_{l,t}$ repeats the characteristics of the lender bank 1 at t, n times to form the first n rows of $X_{l,t}$; the characteristics of the lender 2 at t, n times to form the next n rows of $X_{l,t}$ and so on.

[7] Following common practice, we row-normalise $\widehat{W}$, that is, $\sum_j \widehat{w}_{i:j,k:l} = 1$.

[8] For the normalization, we follow LeSage and Chih (2018) and do a doubly-stochastic normalisation (according to which, the row and column sums of $\widehat{W}$ are unity). This is without loss of generality, since the to-be presented estimation results are not sensitive to the type of normalisation we use (LeSage and Pace, 2009).

[9] Aquaro et al. (2015) allow the spatial autoregressive parameters to differ across units and derive the conditions needed for identification and consistent estimation under parameter heterogeneity.

figure that is comparable to the 6.8% that the interbank market represents in a sample of 225 banks all over the world (source: Bankscope data, for the same period).

Regarding the interbank connection matrix, one could question the appropriateness of having a single connection matrix, as opposed to considering the evolution of this matrix over time. The reasons for our choice are three-fold. First, the type of connections we aim at identifying with our methodology are long-term or permanent interactions, which we then use to weight observations when estimating the spatial autoregressive model. Second, this is to avoid introducing an undesirable degree of randomness in the analysis. Last, having a single interbank connection matrix is justified in our application by the fact that the Chilean interbank market is a relatively stable market, with almost the same banks participating in the market over time and showing stable market shares. Supporting the latter, as a robustness check, we compute two interbank connection matrices, one relying on data for the period 2009–2012 and the other for the period 2013–2016. We find that the correlation coefficient between the two previously defined matrices was 94%, whereas the correlation coefficients of each of these matrices with the (baseline) one using the whole sample period, was 90% and 92%.[10]

It is important to add that because we define as significant interbank connections those for which the pair-wise correlation of bilateral interbank exposure across time is sufficiently strong, by construction, our interbank connection matrix will be sparse (that is, containing many zero off-diagonal elements). The difference with respect to the density or sparsity of the interconnection matrix has also consequences for the choice of the estimation method. If the number of zero off-diagonal elements in the connectivity matrix is low, ordinary least squares can be used. Instead, if the number of zero off-diagonal elements is high, either maximum likelihood, instrumental variables or generalized method of moments are required (Elhorst et al., 2018). In particular, in our application, the endogeneity of the interbank connection matrix requires a quasi-maximum likelihood procedure for consistent estimation.

3. Results

Section 3 starts by presenting the interbank connection matrix, which results from applying the methodology described in Section 2.2. Second, it shows the spatial autoregressive model estimates, first, assuming a single and then, heterogenous spatial autoregressive parameters. For comparison, Appendix A.6 reports the panel estimation results, supposing independent observations between banks participating in the Chilean interbank market. Finally, it provides an application of our model estimates, by examining an episode of liquidity shortage experienced by one Chilean (Section 3.3).

3.1. Estimation of the interbank connection matrix

Fig. 1 depicts the estimated interbank connection matrix, with black colored entries representing the non-zero elements or significant interbank connections. To better display these connections, we order the rows and columns of the matrix by lender bank. Table A3, in the appendix, reports some additional metrics of $\widehat{\mathrm{W}}$. Second, by examining the significant interbank connections in $\widehat{\mathrm{W}}$, we characterize the way banks interact in the interbank market.

From the estimation of the interbank connection matrix, $\widehat{\mathrm{W}}$, there are two elements to highlight. To begin with, Fig. 1 shows that $\widehat{\mathrm{W}}$ is a reciprocal and sparse matrix, with the mean of the significant interbank connections being 0.57 (Table A3, in the appendix). This is indicating that on average, a bilateral interbank position is connected with less than one different position, with the maximum number of significant connections being six. Importantly, the fact that the peer groups in our estimated interbank connection matrix are of different sizes and partially overlap are necessary and sufficient conditions to identify the endogenous peer effects of interest (Bramoullé et al., 2009).[11]

Second, the great majority of the statistically significant interbank connections are due to significantly positive pairwise correlations. Indeed, 58 out of the 60 distinct significant interbank connections arise from significantly positive pairwise correlations. The latter is thus showing that in most of the cases, the lending/borrowing choices in the Chilean interbank market which are connected tend to move in the same direction. Without loss of generality, in what follows, we focus on the significantly positive interbank connections.

An advantage of estimating $\widehat{\mathrm{W}}$ is that, by examining the banks present in each dyadic forming the four-tuple $i:j,k:l$, we can give an economic interpretation to the statistically significant interbank connections and this way, characterize the manner banks interact in the interbank market. From the examination of the $\widehat{\mathrm{W}}$, we identify four types of significantly positive interbank connections.

First, we identify the reciprocal interaction, according to which bank i is the same bank than bank l and bank j coincides with bank k. Bank i lending to bank j significantly connected to bank j lending to bank i thus implies a reciprocal interaction between the two banks. The second type is the common lender interaction, which requires that bank i and bank k are the same financial institution: Bank i lending to bank j connected with bank i lending to bank l defines a common lender interaction.

Third, we distinguish the common borrower interaction type, for which we need that bank j equals bank l. Finally, we identify the

[10] We would like to thank an anonymous referee for suggesting this robustness check.

[11] Bramoullé et al. (2009) show that for identification, the matrices I, W, and W^2 must be linearly independent, with I being the identity matrix and W the interaction matrix. An easy way to check whether these three matrices are linearly independent is the following: First, vectorize each matrix, that is, stack its columns on top of each other. Second, verify whether the matrix formed by concatening these stacked vectors has rank three. In this paper, we satisfy the condition of rank three, hence, I, $\widehat{\mathrm{W}}$ and $\widehat{\mathrm{W}}^2$ are linearly independent.

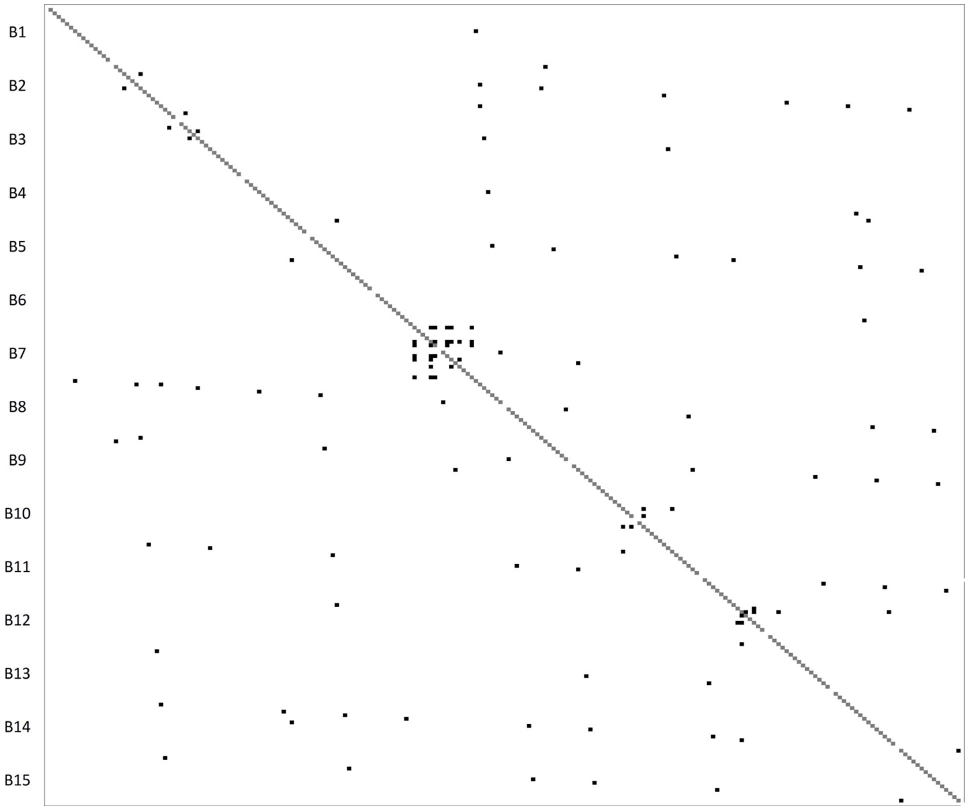

Fig. 1. Interbank connection matrix $\widehat{\mathrm{W}}$. *Notes*: The figure depicts the interbank connection matrix $\widehat{\mathrm{W}}$, based on the significant pairwise correlations of the bilateral interbank positions, according to the Holm procedure. Under this procedure, the non-zeros of $\mathrm{W} = (w_{i:j})$ can consistently be estimated by $\widehat{w}_{i:j,k:l} = I\left(\left|\widehat{\rho}_{i:j,k:l}\right|\rangle\frac{c_p(N)}{\sqrt{T}}\right)$, with $c_p(N) = \Phi^{-1}\left(1 - \frac{p}{2\times f(N)}\right)$, p is the pre-specified overall size of the test, $\Phi^{-1}()$ is the inverse of the cumulative standard normal distribution and $f(N)$ is such that it increases linearly in N. After computing the correlation of the de-factored bilateral interbank positions, we set $p = 0.05$ and order $\left|\widehat{\rho}_{i:j,k:l}\right|$ in a descending manner. Denote the largest value of $\left|\widehat{\rho}_{i:j,k:l}\right|$ by $\left|\widehat{\rho}^1\right|$, the second largest by $\left|\widehat{\rho}^2\right|$ and so on. This way, we obtain the ordered sequence $\left|\widehat{\rho}^s\right|$ for $s = 1, 2, \ldots, N^2$. Finally, let $f(N) \equiv N - s + 1$. Two bilateral interbank positions $i:j$ and $k:l$, with associated $\left|\widehat{\rho}^s\right|$, are connected (that is, $\widehat{w}_{i:j,k:l} = 1$) if $\left|\widehat{\rho}^s\right|\rangle T^{-1/2}\Phi^{-1}\left(1 - \frac{p/2}{N-s+1}\right)$; otherwise, they are unconnected ($\widehat{w}_{i:j,k:l} = 0$). Dimension of the matrix 15×15. B.1 to B.15 stand for banks 1 to 15. Data from Superintendency of Banks and Financial Institutions and Central Bank of Chile.

intermediation interaction type, according to which bank j and bank k need to be the same financial institution: Bank i lending to bank j connected with bank j lending to bank l thus defines an intermediation interaction, with bank j being the intermediary bank.[12] Fig. 2 depicts the significant interbank connection types we have identified. To fix ideas and further illustrate the identified significant interbank connections, Appendix A.5 provides an example with six banks.

To dig into the characteristics of the identified interbank connections, Table 3 reports the frequency with which each interaction type occurs, relative to the total number of significantly positive interbank connections. The table shows two interesting findings. First, that the reciprocal and the common lender types of interactions dominate, with both of them accounting for more than 90% of the significantly positive interbank connections. The second result regards the asymmetric character of the peer effects, in the sense that there are many common lenders but few common borrowers. One way to interpret this second finding is that it may be indicating that lenders being part of the common lender interactions differ in their decisions when choosing which banks to lend.

In order to examine the characteristics of the banks present in the distinct bilateral interbank positions being part of each connection type, we classify the 210 interbank positions in our dataset into the four identified interbank connection types. Starting with the characteristics of the banks present in the positions being part of the common lender interactions, we find that all lenders in this type are commercial banks participating in all market segments. As a matter of fact, four out of the six distinct lenders involved are

[12] Regarding the two significant interbank connections which arise from significantly negative pairwise correlations, in one of them, we do not distinguish any clear pattern, whereas in the other one, we find that $j = k$. We refer to the latter case as countercyclical lending, because during the period 2009–2012, the amount that bank i has lent to bank j has tended to move in the opposite direction with respect to the bilateral interbank position between lender j and borrower l.

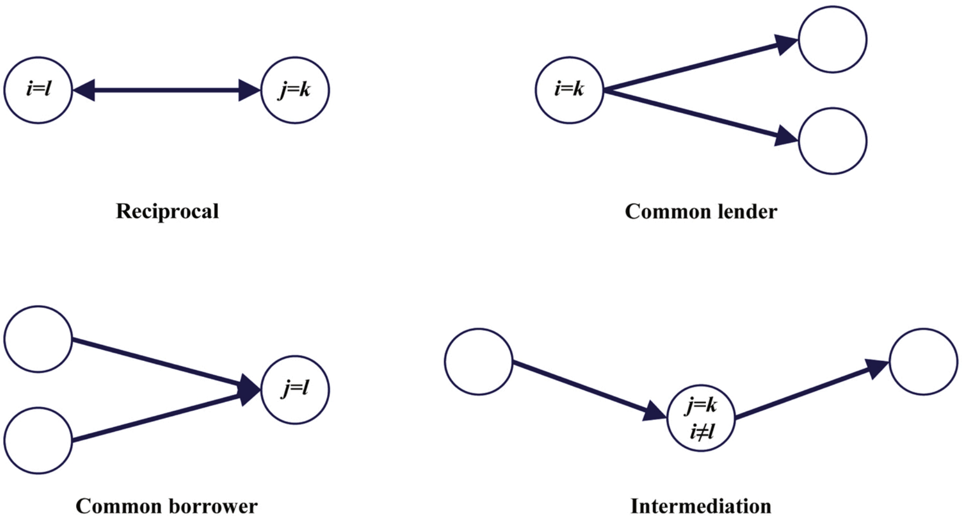

Fig. 2. Types of significantly positive interbank connections. *Notes*: The figure illustrates the significantly positive interbank connections we have identified when estimating $\widehat{\mathrm{W}}$ (see the procedure for estimating the matrix at A.3.3). We identify four types of significantly positive interbank connections. First, we identify the reciprocal interaction, according to which bank i is the same bank than bank l and bank j coincides with bank k. Bank i lending to bank j significantly connected to bank j lending to bank i thus implies a reciprocal interaction between the two banks. The second type is the common lender interaction, which requires that bank i and bank k are the same financial institution: Bank i lending to bank j connected with bank i lending to bank l defines a common lender interaction. Third, we distinguish the common borrower interaction type, for which we need that bank j equals bank l. Finally, we identify the intermediation interaction type, according to which bank j and bank k need to be the same financial institution: Bank i lending to bank j connected with bank j lending to bank l thus defines an intermediation interaction, with bank j being the intermediary bank. The bubbles contain the conditions on $\widehat{w}_{i:j,k:l}$ for each type to hold. Data from Superintendency of Banks and Financial Institutions and Central Bank of Chile.

Table 3
Frequency table of the significantly positive interbank connection types.

Interaction type	Condition on $\widehat{w}_{i:j,k:l}$	Nb of cases	Freq
Reciprocal	$i = l$ and $j = k$	30	52
Common lender	$i = k$	23	40
Common borrower	$j = l$	2	3
Intermediation	$j = k$ and $i \neq l$	2	3
No pattern	–	1	2
Nb of pos connect		58	

Notes: The table reports the number of cases and the frequency with which the significantly positive interbank connection types that we have identified when estimating $\widehat{\mathrm{W}}$, occur (see the procedure for estimating the matrix at A.3.3). We identify four types of significantly positive interbank connections. First, we identify the reciprocal interaction, according to which bank i is the same bank than bank l and bank j coincides with bank k. Bank i lending to bank j significantly connected to bank j lending to bank i thus implies a reciprocal interaction between the two banks. The second type is the common lender interaction, which requires that bank i and bank k are the same financial institution: Bank i lending to bank j connected with bank i lending to bank l defines a common lender interaction. Third, we distinguish the common borrower interaction type, for which we need that bank j equals bank l. Finally, we identify the intermediation interaction type, according to which bank j and bank k need to be the same financial institution: Bank i lending to bank j connected with bank j lending to bank l thus defines an intermediation interaction, with bank j being the intermediary bank. Nb of cases stands for the number of distinct cases. Freq stands for observed frequency, that is, number of cases over the total number of significantly positive interbank connections (58), in percent. Nb of pos connect refers to the total number of distinct significantly positive interbank connections. Data from Superintendency of Banks and Financial Institutions and Central Bank of Chile.

medium-sized commercial banks, accounting for 19 of the 23 significantly positive interbank connections with a common lender. Regarding the borrower banks concerned, the great majority of them are commercial banks (22 out of the 23 significant interbank connections involve commercial borrower banks). Furthermore, these borrower banks are more heterogeneous in terms of size and they tend to be larger (relative to the lender banks being part of the common lender interactions). Supporting the latter, we run a mean comparison test comparing the assets of the borrowers and those of the lenders in the common lender interactions and find that the mean differences between the two groups (assets of borrowers versus assets of lenders) are positive and statistically significant.

Table 4 exhibits an additional interesting finding, which is that the five lender banks in the common lender interaction type make

Table 4
Mean interest rate differences (in basis points), by lender bank in the common lender interaction type.

	Lender banks					
	1	2	3	4	5	All
Interest rate difference (BP)	34.40	26.90	16.90	16.40	36.70	45.00
Observations						
Common lender sig connection = 1	336	86	273	92	335	2303
Common lender sig connection = 0	88	873	635	279	776	1470

Notes: The table reports, by lender bank in the common lender connection type, the whole sample mean difference between the weighted average interest rates computed over the bilateral interbank positions being part of the common lender interaction type and over the remaining bilateral interbank positions. The common lender interaction requires that bank i and bank k are the same financial institution: Bank i lending to bank j connected with bank i lending to bank l defines a common lender interaction. For the comparison, we only consider bilateral interest rates of term deposits, for which we have information. We use a data set of bilateral interest rates of term deposits issued and kept by banks, during the period 2009–2016. We then compute the weighted average of the bilateral interest rates, weighted by the market value of each term deposit. To avoid the influence of outliers, we exclude observations outside the 95% confidence interval of the benchmark wholesale market term deposit rate. BP stands for basis points. Common lender sig connection = 1 corresponds to the total number of observations for the bilateral interbank positions being part of the common lender interaction type. Common lender sig connection = 0 corresponds to the total number of observations for the bilateral interbank positions not being part of the common lender interaction type. Data from Superintendency of Banks and Financial Institutions and Central Bank of Chile.

more money when lending to the banks with which they are connected, according to the common lender interaction type (we had to exclude one lender bank, because the number of observations was too small). This is because the mean differences of the weighted average interest rates computed over the distinct bilateral interbank positions being part of the common lender interaction type and over the remaining bilateral interbank positions are always greater than zero. Furthermore, with one exception, the differences are statistically significantly different from zero.

The way we read the previous finding is that lenders in the common lender interactions provide a stable source of funding to the borrower banks involved, thus resulting in these lenders having the ability to charge higher interest rates in exchange. Supporting the previous interpretation, Table 5 shows that the amounts traded in the distinct bilateral interbank positions being part of the common lender interactions (over the sample period) are less dispersed (as measured by the difference between the percentiles 75 and 25 of these bilateral interbank positions, relative to the median) than the amounts traded in the remaining bilateral positions involving the same lender banks. The latter finding holds both for each lender bank individually and for the set of five lender banks in the common lender interaction type.

Concerning the reciprocal interactions, Table 6 shows that treasury banks, according to Jara and Oda (2015)'s bank categories, have the largest number of reciprocal interactions and also, that their share is larger, relative to the fraction they represent in the bilateral interbank positions not being part of the reciprocal interactions. Intuitively, a bank often lending to and borrowing from the same bank may be indicating that the two banks have a relation, in Cocco et al. (2009)'s terminology. As Cocco and coauthors show, relations can allow banks to insure against liquidity risk in the presence of market frictions, such as transaction and information costs.

To verify whether treasury banks rely more on relations, we follow Cocco and coauthors and compute lender and borrower preference indices (LPI and BPI, respectively).[13] The way to read these indices is that the larger the lender (borrower) preference index, the more likely it is that lender i lends to (borrower j borrows from) a reduced number of borrowers (lenders). Table 7 compares the mean LPI and BPI of banks in the distinct bilateral interbank positions being part of the reciprocal interactions *vis-a-vis* the same indices computed over the remaining bilateral interbank positions, distinguishing by banks' categories.

Table 7 confirms that treasury banks in the bilateral interbank positions which we classify as belonging to the reciprocal type, lend to and borrow from a smaller number of counterparties, relative to the mean indices that treasury banks register when considering the remaining bilateral interbank positions (and relative to the mean indices of the bilateral interbank positions involving the other banks' categories). In addition, the mean difference between the LPI and BPI indices for treasury banks in the two groups of bilateral interbank positions is statistically significant.[14] Furthermore, because treasury banks tend to be small banks, our results are consistent with Cocco et al. (2009)'s finding that smaller banks rely more on relations.

Wrapping up, the estimation of the interbank connection matrix allows us to characterize, in a stylized manner, the way banks interact in the Chilean interbank market. However, at this stage, we cannot determine whether the significant interbank connections we have identified do reflect peer effects or are simply the result of independent banks' profit maximization/diversification strategies. That is precisely the objective of the next section: Estimate the spatial autoregressive models. If peer effects do matter, we should then observe that the spatial autoregressive parameters measuring the strength to which banks' lending and borrowing choices in the interbank market are connected to each other, are significant and non-negligible.

[13] More specifically, for every lender i and every borrower j, we calculate the lender (borrower) preference index of bank i (j) as the ratio of total funds that bank i has lent to bank j (bank j has borrowed from bank i) during a given month, over the total amount of funds that bank i has lent in (bank j has borrowed from) the interbank market during that same month. We then average the bank-specific indices over the period of reference.

[14] A caveat of the exercise though is that the same treasury banks are in the two disjoint groups of bilateral interbank positions.

Table 5
Comparing the dispersion of bilateral interbank positions being part of the common lender interactions and the remaining bilateral positions involving the same lender banks.

	Interbank positions in the common lender interactions			Rest of bilateral interbank positions		
	Mean	$\frac{P_{75}-P_{25}}{P_{50}}$	Obs	Mean	$\frac{P_{75}-P_{25}}{P_{50}}$	Obs
Lender 1	16.67	0.74	174	8.71	4.31	1740
Lender 2	320.00	2.08	348	89.66	21.42	1566
Lender 3	14.12	2.67	609	2.20	327.00	1305
Lender 4	20.46	3.23	261	11.44	6.17	1653
Lender 5	28.78	1.41	435	9.11	2.35	1479
All	77.02	2.20	1827	24.65	6.49	7743

Notes: The table reports the number of observations, the mean and the dispersion (as measured by the difference between the percentiles 75 and 25 of the bilateral interbank positions, relative to the median) for the amounts traded in the bilateral interbank positions being part of the common lender interactions and the amounts traded in the remaining bilateral positions involving the same lender banks. P_{25}, P_{50}, and P_{75} correspond to the percentile 25, 50, and 75, respectively, of the corresponding empirical distributions. Obs stands for observations. The common lender interaction requires that bank i and bank k are the same financial institution: Bank i lending to bank j connected with bank i lending to bank l defines a common lender interaction. Data from Superintendency of Banks and Financial Institutions and Central Bank of Chile.

Table 6
Frequency of banks' categories and the average frequency per bank (in percent), distinguishing between the bilateral interbank positions which we classify as belonging to the reciprocal interactions and the remaining bilateral interbank positions.

Banks' categories	Reciprocal interactions		Non-reciprocal interactions	
	Freq	Avg freq per bank	Freq	Avg freq per bank
Big	25	6.25	27	6.75
Medium-sized	27	3.86	55	7.86
Treasury	43	14.33	11	3.67
Retail	5	5	7	7
Number of int positions	60		150	

Notes: The table reports the frequency of banks' categories and the average frequency per bank, distinguishing between the bilateral interbank positions which we classify as belonging to the reciprocal interaction type and the remaining bilateral interbank positions. The column Avg freq per bank exhibits the frequency of a bank category over the total number of distinct banks in that bank's category and in that subset of bilateral interbank positions. Avg stands for average and int, for interbank. We identify the reciprocal interaction, according to which bank i is the same bank than bank l and bank j coincides with bank k. Bank i lending to bank j significantly connected to bank j lending to bank i thus implies a reciprocal interaction between the two banks. Banks' categories are big and medium-sized commercial banks, treasury and retail banks, according to Jara and Oda (2015)'s classification. Reciprocal interactions and Non-reciprocal interactions refer to the distinct bilateral interbank positions being part and not being part of the reciprocal interaction type, respectively. Number of int positions stands for number of bilateral interbank positions. Data from Superintendency of Banks and Financial Institutions and Central Bank of Chile.

Table 7
Mean LPI and BPI of the banks in the bilateral interbank positions being part and not being part of the reciprocal interactions, distinguishing by banks' categories.

Bank categories	Reciprocal interactions		Non-reciprocal interactions	
	LPI	BPI	LPI	BPI
Big	5.67	4.66	7.60	7.81
Medium-sized	5.15	4.88	7.26	7.26
Treasury	8.20	8.06	5.37	5.45
Retail	4.08	2.28	7.73	8.23
Total	6.55	6.07	7.19	7.29

Notes: The table displays the mean lender preference index (LPI) and borrower preference index (BPI) of banks in the bilateral interbank positions being part and not being part of the reciprocal interactions, distinguishing by banks' categories. We identify the reciprocal interaction, according to which bank i is the same bank than bank l and bank j coincides with bank k. Bank i lending to bank j significantly connected to bank j lending to bank i thus implies a reciprocal interaction between the two banks. Banks' categories are big commercial banks, medium-sized commercial banks, treasury and retail banks, according to Jara and Oda (2015)'s classification. Reciprocal interactions and Non-reciprocal interactions refer to the distinct bilateral interbank positions being part and not being part of the reciprocal interaction type, respectively. Data from Superintendency of Banks and Financial Institutions and Central Bank of Chile.

3.2. Quantifying the importance of peer effects

We now present the model estimates of the spatial autoregressive panel data models. The dependent variable corresponds to the monthly evolution of the lending/borrowing positions in the interbank market. The bank-specific characteristics are the proportion of non-performing loans, the return on assets, the foreign liabilities, bank deposits, total loans and the capital adequacy ratio. All control variables are de-factored,[15] standardized and lagged one month. Specifically, Table 8 presents the estimates of the SAR model, assuming a single autoregressive parameter. Table 9, in turn, reports the estimates of the HSAR model, allowing for heterogenous coefficients.

3.2.1. The homogeneous spatial autoregressive model

The first important conclusion to extract from Table 8 is that the significant interbank connections we have identified when estimating $\widehat{\mathrm{W}}$ do reflect peer effects: The coefficient estimate for $\widehat{\psi}$, which measures the strength of peer effects in banks' lending and borrowing choices in the interbank market is significant and positive. On top of that, the estimated $\widehat{\psi}$ of 0.36 reveals that the (average) influence of other banks' lending and borrowing choices in the interbank market on the lending/borrowing position of any two given banks is considerable. This is because $\widehat{\psi}$ should range between $(-1, 1)$, with higher values reflecting stronger peer effects.

Second, Table 8 shows that R^2 coefficient equals 0.17, well above the 0.02 we obtain when assuming that the homogeneous spatial autoregressive term is zero (Table A6 in the appendix). Hence, it reinforces the finding that peer effects do influence banks' lending/borrowing choices in the Chilean interbank market.

Third, although the overall fit of the model is moderate, this is due to the defactoring. In fact, if we were to estimate the same model specification than in Table 8, but without de-factoring the observations, we would obtain a R^2 coefficient of 0.82. The latter is thus indicating that unobserved common factors considerably affect banks participating in the Chilean interbank market. The implication is that it is necessary to first account for these factors, before investigating the influence of peers on banks' lending/borrowing choices in the interbank market. Interestingly, relying on a dataset of bilateral interbank positions between German banks over the period 2000–2006, Craig et al. (2014) also highlight the importance of unobserved cross-sectional dependence, in their case, to model the influence of interbank connectedness on the probability of distress of individual banks.

Fourth, the lender and borrower-specific characteristics we consider here are significant determinants of the de-factored bilateral interbank positions. Specifically, we find that banks with a larger proportion of non-performing loans lend more in the interbank market. A possible interpretation is that the interbank market is perceived as a safe investment and therefore, as a way to compensate the higher risk being materialized in the credit market. An unreported analysis provides some support to this hypothesis: Specifically, we examine the relation between the rate at which banks lend in the interbank market and the fraction of non-performing loans of the lender banks. Interestingly, we find that banks with more non-performing loans lend at a lower rate, indicating, possibly, that they provide loans to banks focusing on those with low credit risk. Afonso et al. (2014) report a similar finding and argue that it can be a way to send a positive signal to the market.[16]

Furthermore, Table 8 shows that banks with better investment opportunities lend more and borrow less in the interbank market. A possible interpretation is that banks with more profitable investment projects have lower funding costs, which allows them to lend more in the interbank market. In addition, Table 8 shows that the larger the stock of deposits the bank has, the less it borrows from the interbank market. Finally, a higher fraction of foreign liabilities reduces both interbank lending and borrowing. While the reduction in borrowing is easy to explain due to substitution in funding sources, the reduction in lending is less intuitive. A possible explanation is that banks which have access to foreign funding have a lower need to get involved in reciprocal relations that would secure them local funding; therefore, they can lend less in the interbank market.[17]

Appendix A.7 describes the two robustness checks we conduct. Overall, they show that results in Table 8 are robust to alternative model specifications and to alternative weight matrices. Hence, although the SAR model is not our preferred model, we can rely on it as a first indication of the importance of peer effects on banks' lending/borrowing choices in the Chilean interbank market.

3.2.2. The heterogeneous spatial autoregressive model

Allowing for parameter heterogeneity, Table 9 presents the model estimates of the HSAR. More precisely, it reports the overall mean, median and standard deviation of the $\boldsymbol{\psi}_{i:j}$, β_{il}, β_{ib} estimates, the proportion of bilateral interbank positions with statistically significant coefficient estimates (at 10% significance level), as well as the mean, median and standard deviation, computed only over the significant coefficient estimates.

Table 9 confirms our previous finding, which is that the significant interbank connections we have identified when estimating $\widehat{\mathrm{W}}$ do reflect peer effects. This is because the overall mean of the HSAR parameter estimates equals 0.17, with the average $\widehat{\psi}_{i:j}$ increasing to

[15] Since we reject the null of weak cross-sectional dependence, both in the case of the bilateral interbank positions, as well as the bank-specific balance sheet characteristics, we model the implied strong cross-sectional dependence, by means of *m*-factor models, yielding the de-factored observations. See the appendix for the technical details.

[16] We are grateful to one of our anonymous referees for suggesting this exercise.

[17] Although a direct comparison of the least-square coefficient estimates in Table A6 with the ML parameter estimates in Table 8 is not valid, we can still compare the signs of the coefficient estimates in both estimations, which depend on the sign of the trace of $(\mathrm{I_N} - \widehat{\psi} \times \widehat{\mathrm{W}})^{-1}$, with $\mathrm{I_N}$ being the $N \times N$ identity matrix. Because the previous expression is positive, we know that the direct comparison of the signs of both sets of estimated coefficients is valid.

Table 8
Determinants of the bilateral interbank positions, SAR model. ML estimates, applied to the de-factored lending/borrowing interbank positions.

Variable	Coefficient	Asymptotic *t*-stat	*P*-value
ψ	**0.37**	50.25	0.00
Lender characteristics			
Non-performing loans	**1.44**	2.74	0.01
Return on assets	**0.12**	2.13	0.03
Foreign liabilities	− **1.55**	− 2.99	0.00
Bank deposits	**1.41**	2.53	0.01
Total loans	**1.81**	3.25	0.00
Capital adequacy ratio	− 0.18	− 0.32	0.75
Borrower characteristics			
Non-performing loans	− 0.85	− 1.61	0.11
Return on assets	− **1.10**	− 2.09	0.04
Foreign liabilities	− **1.70**	− 3.29	0.00
Bank deposits	− **1.73**	− 3.10	0.00
Total loans	**1.00**	1.79	0.07
Capital adequacy ratio	− 0.74	− 1.32	0.19
Observations	18,270		
R^2	0.17		
Log likelihood	− 102,974		
Number of bilateral interbank positions	210		
Dyadic fixed effects	YES		

Notes: The table reports the spatial panel model estimates with spatially lagged dependent variable, and fixed effects for the interbank positions and time periods. The dependent variable is the de-factored bilateral lending/borrowing positions in the interbank market (de-factored by means of a four-factor model). All the control variables are de-factored, standardized and lagged one period. Bilateral exposure includes include interbank loans, current accounts, repurchase agreements, derivatives, term deposits, bank bonds, interbank loans with collateral, and operations in the course of liquidation. Non-performing loans are loans where the borrower is 90 days past due overt total loans. Return on assets corresponds to the return on assets before tax. Foreign liabilities correspond to foreign liabilities. Bank deposits correspond to term deposits owned by individuals, firms, and financial institutions. Total loans correspond to commercial, consume, and other loans. Capital adequacy ratio is the ratio of a bank's capital in relation to its risk weighted assets and current liabilities. Interest rate term deposits correspond to the bilateral interest rate of outstanding term deposits. Total assets correspond to the total assets. In bold: Significant coefficient estimates at 10% significance level. Asymptotic *t*-stat stands for the asymptotic test statistic *t* and *P*-value stands for probability value. Data for January 2009 to March 2016. Data from Superintendency of Banks and Financial Institutions and Central Bank of Chile.

0.71 (which is close to the maximum value of 1), when we only consider the statistically significant parameter estimates. Furthermore, the result that 35% of the $\widehat{\psi}_{i:j}$ estimates are statistically significant (first row of results in Table 9) also reinforces the above result and on top, it highlights the attractiveness of having a methodology that allows for various degrees of intensity of the peer effects. Note that it also justifies distinguishing in Table 9 between the overall statistics and the ones computed only over the statistically significant estimates.

Focusing on the significant estimated coefficients for the balance sheet characteristics, β_{il} and β_{ib}, we observe that, with three exceptions, the signs of the mean coefficient estimates in Table 9 coincide with those reported in Table 8. Precisely, we continue to find that banks with a larger proportion of non-performing loans lend more and borrow less in the interbank market; that the more banks borrow from abroad, the less they lend in the domestic interbank market; last, that the larger the stock of deposits a bank has, the less it needs to borrow from the interbank market. In contrast to the SAR model estimates, Table 9 reveals that banks with better investment opportunities lend less and borrow more in the interbank market. The latter is indicating that banks with more profitable investment projects may have alternative ways of placing their liquidity (which in turn would explain why they lend less in the interbank market) and may have lower funding costs (which in turn would allow them to borrow more from other banks in the interbank market).

In order to investigate the robustness of the previous results, we conduct three robustness checks: First, we consider some alternative model specifications (namely, excluding the capital adequacy ratio, as well as expressing non-performing loans, foreign liabilities, bank deposits and total loans, as proportions of banks' total assets); second, we scale the dependent variable by the sum of assets of the lender and borrower banks in each bilateral position (and we keep the same bank-specific characteristics than the model specification in Table 9); last, we rely on two alternative weight matrices (a matrix based on banks' size and one based on banks' market focus, see Appendix A.7 for details). All robustness checks confirm that the results in Table 9 are robust. In particular, in the third robustness check, we find that the overall mean and median of the HSAR parameter estimates continue to be positive and close together, although they now range between 0.10 and 0.20. In addition, we still observe that only a subset of the bilateral interbank positions have statistically significant spatial autoregressive parameter estimates and that some mean estimates of the bank-specific characteristics are not precisely estimated.

A natural following question would be which bank characteristics make banks more likely to be sensitive to the lending/borrowing

Table 9
Determinants of the bilateral interbank positions, HSAR model. QML estimates, applied to the de-factored lending/borrowing interbank positions.

	Over all coefficients			%Sig (10%)	Over significant coefficients		
	Mean	Median	Std. Dev.		Mean	Median	Std Dev
$\psi_{i:j}$	0.17	0.00	0.40	35%	0.72	0.71	0.17
Lender characteristics							
Non-performing loans	1.27	0.00	18.25	20%	6.80	15.96	33.21
Return on assets	1.80	1.07	17.73	15%	− 1.77	8.95	33.22
Foreign liabilities	− 0.61	− 0.70	15.22	15%	− 2.68	− 10.81	28.13
Bank deposits	6.55	3.94	23.57	18%	23.90	33.47	38.55
Total loans	− 0.95	0.00	41.04	17%	− 12.32	− 34.16	78.61
Capital adequacy ratio	0.61	0.18	15.37	14%	− 1.96	− 16.24	29.03
Borrower characteristics							
Non-performing loans	− 0.45	0.00	18.50	17%	− 2.80	− 11.01	34.39
Return on assets	− 0.10	− 0.56	17.82	18%	0.98	− 10.55	32.99
Foreign liabilities	− 0.39	− 0.97	18.29	16%	1.84	− 8.04	38.85
Bank deposits	− 1.64	− 2.23	18.62	10%	− 8.51	− 8.59	33.44
Total loans	4.85	0.36	34.69	13%	26.01	50.42	69.54
Capital adequacy ratio	− 0.82	− 0.94	14.01	14%	− 2.82	− 12.09	28.03

Notes: This table reports the spatial panel model estimates where the dependent variable is the de-factored bilateral lending/borrowing position in the interbank market (de-factored by means of a four-factor model). All the control variables are de-factored, standardized and lagged one period. Bilateral exposure includes include interbank loans, current accounts, repurchase agreements, derivatives, term deposits, bank bonds, interbank loans with collateral, and operations in the course of liquidation. Non-performing loans are loans where the borrower is 90 days past due overt total loans. Return on assets corresponds to the return on assets before tax. Foreign liabilities correspond to foreign liabilities. Bank deposits correspond to term deposits owned by individuals, firms, and financial institutions. Total loans correspond to commercial, consume, and other loans. Capital adequacy ratio is the ratio of a bank's capital in relation to its risk weighted assets and current liabilities. Interest rate term deposits correspond to the bilateral interest rate of outstanding term deposits. Total assets correspond to the total assets. %Sig (10%) stands for the percentage of bilateral interbank positions with statistically significant coefficients at 10% significance level and Std. Dev. stands for standard deviation. Data for January 2009 to March 2016. The spatial autorregressive parameters of the bilateral interbank positions with no significant interbank connections, which total 122, are set to zero. Data from Superintendency of Banks and Financial Institutions and Central Bank of Chile.

choices of other banks in the Chilean interbank market. To address this point, we examine whether size, ownership and market focus are useful to characterize the lender and borrower banks involved in the heterogeneous $\widehat{\psi}_{i:j}$. Table 10 reports the overall mean, median and standard deviation and the number of observations of the spatial autoregressive parameter estimates, breaking them down by the previous banks' characteristics. Also, the table reports the statistics computed only over the statistically significant ones. To examine banks' size, we rely on bank assets' quartiles.

Table 10 indicates that small, foreign and treasury banks are the most sensitive to the influence of other banks' choices in the Chilean interbank market. Furthermore, when we examine whether the mean spatial autoregressive parameter estimates involving small, foreign or treasury banks are significantly different from the mean $\widehat{\psi}_{i:j}$ involving big, domestic or non-treasury banks, respectively, we find that only for the borrower banks, the mean differences are statistically significant.[18] Oppositely, we do not observe significant differences between lender banks, with and without a given characteristic.

There are two conclusions to derive from the results of the mean comparison tests of the spatial autoregressive parameters: On the one hand, that borrower banks are more dissimilar between themselves (relative to the lenders) at least, in terms of size, nationality and business model. On the other hand, knowing that treasury banks' assets belong to the first quartile of the empirical distribution of banks' assets and that they are foreign banks, an additional conclusion we can derive is that these specific borrower banks are more sensitive to other banks' choices in the Chilean interbank market, because they are smaller and hence, potentially more exposed to the risk of not getting funding from other banks in the Chilean interbank market.

Interestingly, in an unreported descriptive analysis, we find that small banks (with assets belonging to the first asset quartile) also appear to have less credit risk and more capital, as measured by the mean proportion of non-performing loans and capital adequacy

[18] More specifically, for each lender and borrower bank characteristic, we conduct a mean-comparison test, to determine whether the mean of the (non-null) heterogeneous spatial autoregressive parameters involving lender or borrower banks with a given characteristic is statistically different from the mean parameters of lender or borrower banks without the characteristic. In the case of Jara and Oda (2015)'s bank categories, we do the comparison by pairs of categories, whereas for asset quartiles, we compare the first and fourth quartiles. Finally, the mean-comparison tests include all the spatial autoregressive parameter estimates, without distinguishing whether they are significant or not. This is because in some cases, the number of significant estimates is too small to run the test. Considering all the spatial autoregressive parameter estimates to run the mean-comparison tests is without loss of generality, because when focusing on the significant parameter estimates, the mean differences are even bigger.

Table 10
Analysis of the $\psi_{i;j}$ estimates, when we break down by banks' size, ownership and market focus.

Characteristic	Value	Over all coefficients				Over significant coefficients			
		Mean	Median	Std. Dev.	Obs.	Mean	Median	Std. Dev.	Obs.
Quartile of lenders' assets	1	0.21	0.09	0.45	56	0.73	0.72	0.12	14
	2	0.15	0	0.42	56	0.70	0.67	0.20	9
	3	0.12	0	0.31	56	0.65	0.64	0.15	4
	4	0.22	0	0.37	42	0.75	0.82	0.25	7
Quartile of borrowers' assets	1	0.15	0	0.41	56	0.63	0.66	0.14	6
	2	0.08	0	0.24	56	0.60	0.60	0.15	5
	3	0.09	0	0.45	56	0.74	0.76	0.17	10
	4	0.43	0.47	0.81	42	0.78	0.77	0.17	13
If lender is domestic	0	0.19	0	0.43	84	0.74	0.73	0.16	17
	1	0.16	0	0.38	126	0.69	0.68	0.18	17
If borrower is domestic	0	0.23	0	0.44	84	0.76	0.78	0.16	18
	1	0.14	0	0.37	126	0.66	0.67	0.17	16
Lenders' bank category	Big	0.21	0	0.40	56	0.71	0.73	0.25	8
	Medium	0.15	0	0.40	98	0.73	0.73	0.18	14
	Treasury	0.20	0.09	0.44	42	0.71	0.71	0.71	11
	Retail	0.05	0	0.18	14	0.61	0.61	-	1
Borrowers' bank category	Big	0.10	0	0.43	56	0.66	0.69	0.16	12
	Medium	0.10	0	0.36	98	0.65	0.68	0.15	7
	Treasury	0.43	0.47	0.38	42	0.78	0.77	0.17	13
	Retail	0.14	0	0.31	14	0.83	0.83	0.24	2

Notes: The table reports the mean, median, standard deviation and number of observations of the spatial autoregressive parameter estimates, breaking them down by banks' size, ownership and market focus. It also distinguishes whether the parameter estimates are significant or not. Value refers to the values that each variable can take. The variable "If lender is domestic" takes the value of 1 if the lender is a domestic bank. Std. Dev. and Obs. stand for standard deviation and observations, respectively. Bank cat stands for banks' categories, according to Jara and Oda (2015)'s bank classification.

ratio, respectively, relative to big banks (which assets are in the fourth quartile). One way to read the latter is that being well capitalized and having a low exposure to credit risk may be complementary ways to insure against the liquidity risk that small banks face and to increase their probability of survival in the event of a crisis.

Table 11
Analysis of the $\psi_{i;j}$ estimates, when we break down by significantly positive interbank connection types.

Interaction type	Number	Freq
Reciprocal	18	58
Common lender	9	29
Common borrower	2	6
Intermediation	2	6

Notes: The table breaks down the significant $\psi_{i;j}$ estimates by interbank connection types. We identify four types of significantly positive interbank connections. First, we identify the reciprocal interaction, according to which bank i is the same bank than bank l and bank j coincides with bank k. Bank i lending to bank j significantly connected to bank j lending to bank i thus implies a reciprocal interaction between the two banks. The second type is the common lender interaction, which requires that bank i and bank k are the same financial institution: Bank i lending to bank j connected with bank i lending to bank l defines a common lender interaction. Third, we distinguish the common borrower interaction type, for which we need that bank j equals bank l. Finally, we identify the intermediation interaction type, according to which bank j and bank k need to be the same financial institution: Bank i lending to bank j connected with bank j lending to bank l thus defines an intermediation interaction, with bank j being the intermediary bank. Number refers to the number of bilateral interbank positions with significant spatial autoregressive parameter estimates, being part of each interaction type. Freq stands for observed frequency, over the total number of significant spatial autoregressive parameter estimates, in percent.

Last, in order to investigate the mechanisms through which the peers influence banks' lending/borrowing choices in the Chilean interbank market, we now relate the significant spatial autoregressive parameter estimates with the interaction types we identify in

Section 3.1. More precisely, Table 11 reports the number of distinct bilateral interbank positions with significant spatial autoregressive parameter estimates which we classify as being part of each interbank connection type, as well as the fraction that they represent on the total number of significant $\widehat{\psi}_{i:j}$.[19]

Table 11 shows an important finding which is that the reciprocal and the common lender interaction types we have identified in Section 3.1 do reflect peer effects. Furthermore, results show they continue to dominate (relative to the remaining two interbank connection types). This is because the distinct bilateral interbank positions with significant $\widehat{\psi}_{i:j}$, which are part of the reciprocal and the common lender interaction types, account for 58% and 29%, respectively, of the significant spatial autoregressive parameter estimates. Furthermore, the same interbank positions represent 60% (18/30) and 39% (9/23), respectively, of the total number of distinct bilateral interbank positions involved in each connection type.

Concerning the reciprocal interactions, the 58% share that the bilateral interbank positions with statistically significant $\widehat{\psi}_{i:j}$ being part of the reciprocal interaction type have on the total number of significant $\widehat{\psi}_{i:j}$, provides support to the long-run relation motive for the endogenous peer effects, with these relations possibly being some form of cross-insurance between banks. Furthermore, from Section 3.1, we know that treasury banks are the ones having the largest number of these reciprocal interactions and the smallest number of counterparties.

Regarding the mechanisms through which peers being part of the common lender interactions might influence other banks' lending choices, Manski (2000) identifies three channels through which an action chosen by one agent (in our case, a lending decision in the interbank market) may affect the actions of other agents (other cross-exposures in the same market): Expectations, preferences and constraints. In our context, the expectation and preferences channels would be that when determining which bank(s) to lend (or stop lending), lender bank i imitates what another lender bank, say bank m, is doing, because it prefers to act like lender bank m (preference channel) or because lender bank i believes that bank m has superior information (expectation channel). In turn, a constraint interaction might occur if the amount lender bank i lends to j is limited, at least in some way, by the amount bank i lends to l.

While the data we rely on does not allow us to distinguish between the preference and the expectation channels, where we can say something is about the constraint interaction channel: If there were some substitution effect between borrower banks j and l borrowing from lender i, we should observe statistically significant negative pairwise correlations between the interbank cross-exposures $i:j$ and $i:l$. On the contrary, all the common lender connections are due to statistically significant positive pairwise correlations. Therefore, we can argue that the constraint interaction channel is unlikely to play any role in our data.

Wrapping up, the results we exhibit in Tables 9–11 reveal that there is evidence of peer effects and, on top, that there is heterogeneity in the extent to which peer effects matter in the Chilean interbank market. The fact that we propose a framework which offers the necessary flexibility to allow for different degrees of intensity of the peer effects is one of the contributions of this paper, relative to the existing literature, which typically assumes a single parameter to measure the influence of peer effects (for instance, Liedorp et al. (2010), Craig et al. (2014), Silva (2019)). In the next section, we apply our model estimates to examine an episode of liquidity shortage experienced by one Chilean bank in the interbank market.

3.3. Application

The aim of the exercise is to provide an application of our HSAR model estimates for simulation and stress test analyses. For that, we consider an episode of liquidity shortage experienced by one Chilean bank, which took place in the first half of the 2010s. The episode was generated by a non-financial company that was facing financial stress. That company was owned by the same group which owned a medium-sized commercial bank. The group helped the company via the bank, using vehicles whose attachment to regulation was publicly questioned. Concerns about the impact of both the regulatory consequences and the financial operation of the bank resulted in a sharp fall in interbank market funding to this bank and in its stock price. In what follows we refer to this bank as bank A and we denote period T, the start of the liquidity crisis for bank A.

The exercise uses the HSAR parameter estimates $\widehat{\psi}_{i:j}$ to form two groups of bilateral interbank positions involving bank A as a borrower, and the 14 remaining banks as lenders: On the one hand, there is the group of those bilateral positions exhibiting non-zero HSAR parameter estimates. On the other hand, there is the group of bilateral positions with zero HSAR parameter estimates. We refer to the first group as the group of "correlated lender banks to bank A" and the second group as the "uncorrelated lender banks to bank A". It is worth mentioning that the interbank positions involving bank A and having non-zero $\widehat{\psi}_{i:j}$ estimates belong to the common lender interactions.

We study the evolution of total lending to bank A, distinguishing between the two groups of lenders to bank A, over the period 2009–2014. Lending is considered in logarithms and standardized. Results are striking and are depicted in Fig. 3. The figure shows that before period T, the level and the evolution of total lending to bank A was similar between groups. However, since the beginning of the crisis, the behavior of the two groups differed enormously. Correlated lender banks to borrower bank A according to the HSAR model, markedly reduced their lending to bank A, relative to the uncorrelated group of bilateral interbank positions.

The way we interpret these findings is as follows. The change in the relative risks of banks made "correlated lenders" to reduce their exposure to bank A, which is consistent with a herd behavior. Uncorrelated lenders, on the contrary, may have assessed the situation individually and they may have been willing to take on additional risks at the higher return they were receiving. The aggregate result

[19] It is worth mentioning that there are three bilateral interbank positions with significant parameter estimates, which are part of two interaction types. We add each of them to the two interaction types concerned.

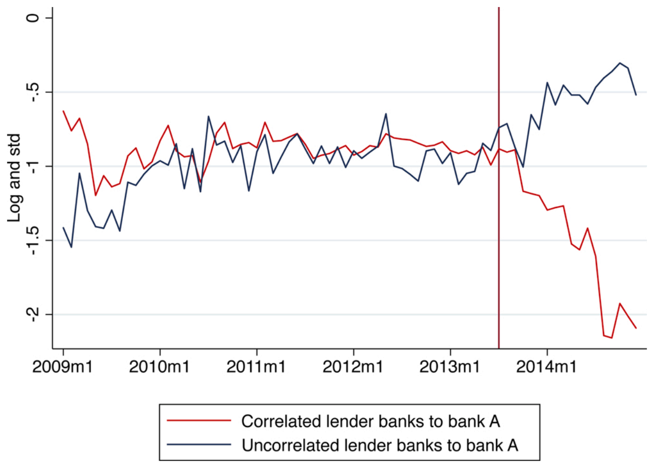

Fig. 3. Total lending to bank A. *Notes*: The figure shows the evolution of total lending to bank A (anonymised bank), in logarithms and standardized, distinguishing between the two groups of lenders to bank A, over the period 2009–2014. The exercise uses the HSAR parameter estimates $\widehat{\psi}_{i;j}$ to form two groups of bilateral interbank positions involving bank A as a borrower, and the 14 remaining banks as lenders: On the one hand, there is the group of those bilateral positions exhibiting non-zero HSAR parameter estimates. On the other hand, there is the group of bilateral positions with zero HSAR parameter estimates. We refer to the first group as the group of "correlated lender banks to bank A" and the second group as the "uncorrelated lender banks to bank A". Data from Superintendency of Banks and Financial Institutions and Central Bank of Chile.

shows an increase in their lending to bank A following period T. The latter is thus indicating that some lender banks in the uncorrelated group may have provided part of the lending lost from the correlated group to bank A.

The example is striking in showing the differences in the behavior of banks. "Correlated lending" can be interpreted as banks that allocate their lending following some portfolio rule or analysis with regularity, such that it is captured in the data. The allocation decisions of other banks may be less regular and, therefore, less predictable. Crucially, our method allows us to capture these regu-

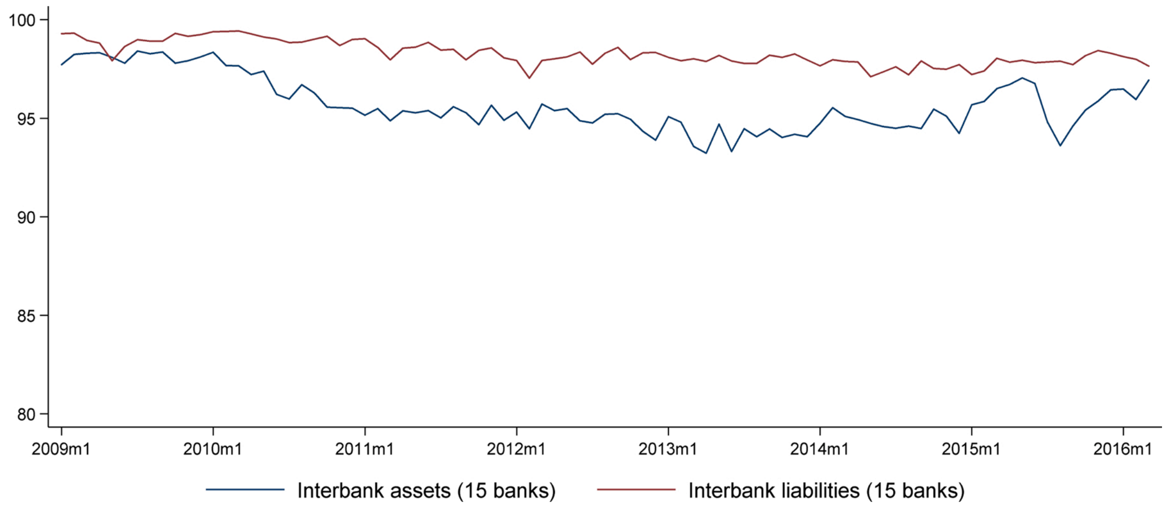

Fig. 4. Total lending to all banks except bank A. *Notes*: The figure shows the evolution of total lending to all banks except bank A (anonymised bank), in logarithms and standardized, distinguishing between the same two groups of lenders (the "correlated lender banks to bank A" and the "uncorrelated lender banks to bank A"), over the period 2009–2014. The exercise uses the HSAR parameter estimates $\widehat{\psi}_{i;j}$ to form the two groups of bilateral interbank positions involving bank A as a borrower, and the 14 remaining banks as lenders: On the one hand, there is the group of those bilateral positions exhibiting non-zero HSAR parameter estimates. On the other hand, there is the group of bilateral positions with zero HSAR parameter estimates. Data from Superintendency of Banks and Financial Institutions and Central Bank of Chile.

larities and hence, assess the potential market impact of changes in the determinants of financial conditions of banks. Results are robust to comparing the differences between the evolution of the average lending of the two groups and the amounts lent to bank A (by each group) over the whole period. As an additional robustness check, we run a falsification test. The aim is to confirm that the group of "correlated lender banks to bank A" reduced their lending only to bank A and not across banks. Specifically, we compute the total lending to all banks except bank A (in logarithms and standardized), distinguishing between the same two groups of lenders. Fig. 4 depicts the results. It shows that the group of lender banks being correlated to bank A did not reduce their lending across all banks in the interbank market but just to bank A.[20]

Therefore, we conclude that the HSAR model estimates provide a unique classification to identify banks which are more likely to herd and/or more prone to be sensitive to the liquidity shortage of bank A. More generally, the exercise shows that we could use the HSAR model estimates to predict which banks would be more likely to be sensitive to the crisis of a given bank in the interbank market and to the behavior of other banks in the same market. The latter is of first order of importance for policy makers with a mandate on financial stability and researchers with an interest on the topic.

4. Conclusions

The main objective of this paper is to propose a flexible framework to identify peers statistically by inferring them from data on interbank cross-exposure. We have access to a rich and granular dataset, containing all interbank loans between 15 banks representing more than 95% of the Chilean interbank market over the period 2009–2016. We exploit this granularity to identify the peers; we then characterise the different types of interactions between banks participating in the market that emerge from our dataset. Our framework is general and easy to implement; hence, it should be of interest to researchers and policy makers with an interest on banks' interconnections.

We show that peer effects are asymmetric, in the sense that there are many common lenders being sensitive to the decisions of their peers but few common borrowers. Also, we find that small and foreign banks are the most sensitive to the lending/borrowing choices of other banks in the same market, possibly because they have long term lending relations with their peers or because they are the more exposed to the risk of not getting funding from other banks in the Chilean interbank market. In an application examining an episode of liquidity shortage experienced by one Chilean bank, we provide evidence in the direction that banks whose lending to a bank in distress is correlated to other interbank relations, behave differently (in particular, sharply cut their lending to the bank in distress) relative to banks which do not show such correlations (which increase their lending to the bank in distress).

Properly identifying peer effects is important for simulation and financial stability analyses; for example, when modelling the likely impact in the interbank market of a crisis of a given bank. The latter is of first order importance when we consider that some types of peer effects may imply that banks move in tandem, which can act as an amplifier of shocks affecting other banks and/or market prices.

One venue of future research could be to apply the same framework to identify peers for other financial institutions participating in alternative markets. Another venue could be to enlarge the sample to include other financial intermediaries, like pension and mutual funds, and study the interaction between them and banks participating in the interbank market. Our methodology can easily be adjusted to include these additional intermediaries.

Appendix A

A.1 Tables

A.2 Figures

A.3 Data transformation and estimation of the interbank connection matrix

This section starts by describing the way we test the null of weak cross-sectional dependence, both for the bilateral interbank positions and for the bank-specific characteristics. Second, since we reject the null, it details the manner we model the implied strong cross-sectional dependence, by means of factor models. Finally, it provides details for the estimation of the interbank connection matrix.

A.3.1 Testing for weak cross-sectional dependence

Because an implicit assumption of any spatial econometrics application is the weak cross-sectional dependence, we need to test whether this assumption holds in our dataset. To do so, we conduct the cross sectional dependence test statistics of Pesaran (2004, 2015) for the bilateral interbank positions, as well as for the control variables. Complementarily, we follow Bailey et al. (2016b) and compute the exponents of cross-sectional dependence for the same set of variables. According to the authors, an exponent of

[20] Furthermore, results continue to hold if in the group of uncorrelated lenders to bank A we only include medium-sized commercial banks. We would like to thank an anonymous referee for suggesting this exercise.

Table A1
Pairwise correlations.

Variables	BP	NPL	ROA	FL	BD	TL	CAR
Bilateral positions (BP)	1.000						
Non-performing loans (NPL)	0.075	1.000					
Return on assets (ROA)	− 0.078	0.037	1.000				
Foreign liabilities (FL)	− 0.001	0.039	− 0.088	1.000			
Bank deposits (BD)	0.104	− 0.060	− 0.107	0.025	1.000		
Total loans (TL)	0.036	0.029	− 0.162	0.066	0.315	1.000	
Capital adequacy ratio (CAR)	− 0.008	0.021	0.220	− 0.115	− 0.181	− 0.128	1.000

Notes: This table reports the pairwise Pearson correlations of the main variables in this study. All the control variables are de-factored, standardized and lagged one period. Bilateral interbank exposure includes include interbank loans, current accounts, repurchase agreements, derivatives, term deposits, bank bonds, interbank loans with collateral, and operations in the course of liquidation. Non-performing loans are loans where the borrower is 90 days past due overt total loans. Return on assets corresponds to the return on assets before tax. Foreign liabilities correspond to foreign liabilities. Bank deposits correspond to term deposits owned by individuals, firms, and financial institutions. Total loans correspond to commercial, consumer, and other loans. Capital adequacy ratio is the ratio of a bank's capital in relation to its risk weighted assets and current liabilities. Total assets correspond to the total assets. Data from Superintendency of Banks and Financial Institutions and Central Bank of Chile.

Table A2
Descriptive statistics.

Variables	Obs.	Mean	Median	Std. Dev.	Max	Min	P_{25}	P_{75}
Panel A: Medium-sized banks								
Bilateral position	8526	25.13	12.60	33.68	282	0	3.53	32.74
Non-performing loans	8526	0.77	0.70	0.53	3.82	0	0.52	0.85
Return on assets	8526	0.94	1.00	0.43	1.78	− 1.16	0.75	1.20
Foreign liabilities	8526	353	320	250	1021	1.97	137	550
Bank deposits	8526	2337	2061	1313	5495	338	1416	3248
Total loans	8526	4382	4069	2544	9646	338	2276	6089
Capital adequacy ratio	8526	12.61	12.37	1.28	17.20	9.16	11.77	13.28
Int. rate term deposits	8526	3.81	3.88	1.74	7.70	0.24	3.21	5.28
Total assets	8526	5451	5033	3319	13,445	357	2893	7403
Panel B: Treasury and retail banks								
Bilateral position	4872	14.81	8.21	17.86	197	0	2.32	22.02
Non-performing loans	4872	0.23	0	0.35	1.23	0	0	0.43
Return on assets	4872	1.55	1.16	1.68	8.35	− 0.69	0.35	2.18
Foreign liabilities	4872	0.95	0	4.72	34.52	0	0	0
Bank deposits	4872	386	376	321	1164	0.01	58.20	651
Total loans	4872	321	167	399	1359	0	0.97	500
Capital adequacy ratio	4872	49.89	22.55	44.75	241	13.45	13.45	240
Int. rate term deposits	4872	3.72	3.84	1.70	7.27	0.12	3.10	5.12
Total assets	4872	751	758	397	1911	108	431	925
Panel C: Big banks								
Bilateral position	4872	110	40.81	160	1144	0	12.89	134
Non-performing loans	4872	1.21	1.21	0.58	2.82	0.41	0.63	1.57
Return on assets	4872	1.37	1.52	0.58	2.43	0.29	0.87	1.82
Foreign liabilities	4872	1017	1072	523	2099	58.34	658	1373
Bank deposits	4872	7675	7660	1878	11,849	4084	6161	9086
Total loans	4872	16,571	15,313	4976	27,512	8669	12,845	20,071
Capital adequacy ratio	4872	12.95	13.10	1.04	15.59	10.50	12.13	13.66
Int. rate term deposits	4872	3.75	3.78	1.69	7.38	0.25	3.16	5.23
Total assets	4872	20,628	20,323	5486	33,726	11,349	16,373	24,659

Notes: This table presents the descriptive statistics of banks' balance sheet characteristics, distinguishing by type of banks (namely, big, medium-sized, treasury, and retail) banks, as classified by Jara and Oda (2015). Bilateral exposure (millions of Chilean Pesos) includes include interbank loans, current accounts, repurchase agreements, derivatives, term deposits, bank bonds, interbank loans with collateral, and operations in the course of liquidation. Non-performing loans are loans where the borrower is 90 days past due overt total loans. Return on assets corresponds to the return on assets before tax. Foreign liabilities correspond to foreign liabilities (millions of Chilean Pesos). Bank deposits correspond to term deposits owned by individuals, firms, and financial institutions (millions of Chilean Pesos). Total loans correspond to commercial, consume, and other loans (millions of Chilean Pesos). Capital adequacy ratio is the ratio of a bank's capital in relation to its risk weighted assets and current liabilities. Interest rate term deposits correspond to the bilateral interest rate of outstanding term deposits. Total assets correspond to total assets (millions of Chilean Pesos). Obs., Std. Dev., Min and Max stand for observations, standard deviation, minimum and maximum, respectively. Int. stands for interest. P_{25} and P_{75} correspond to the percentile 25 and 75, respectively, of the corresponding empirical distribution. Data from January 2009 to March 2016. Data from Superintendency of Banks and Financial Institutions and Central Bank of Chile.

Table A3
Descriptive statistics of the interbank connection matrix.

Characteristic	
Number of principal components in defactoring	4
Total number of non-zero elements	120
Density	0.27%
Share interbank positions without significant connections	58.10%
Descriptive statistics:	
Mean	0.57
Maximum	6
25th percentile	0
50th percentile	0
75th percentile	1

Notes: The table reports some characteristics and descriptive statistics of the interbank connection matrix $\widehat{W}$, based on the significant pairwise correlations of the bilateral interbank positions, according to the Holm procedure. Under this procedure, the non-zeros of $W = (w_{i:j})$ can consistently be estimated by $\widehat{w}_{i:j,k:l} = I\left(|\widehat{\rho}_{i:j,k:l}|\rangle\frac{c_p(N)}{\sqrt{T}}\right)$, with $c_p(N) = \Phi^{-1}\left(1-\frac{p}{2\times f(N)}\right)$, p is the pre-specified overall size of the test, $\Phi^{-1}()$ is the inverse of the cumulative standard normal distribution and $f(N)$ is such that it increases linearly in N. After computing the correlation of the de-factored bilateral interbank positions, we set $p = 0.05$ and order $|\widehat{\rho}_{i:j,k:l}|$ in a descending manner. Denote the largest value of $|\widehat{\rho}_{i:j,k:l}|$ by $|\widehat{\rho}^1|$, the second largest by $|\widehat{\rho}^2|$ and so on. This way, we obtain the ordered sequence $|\widehat{\rho}^s|$ for $s = 1,2,\ldots,N^2$. Finally, let $f(N) \equiv N - s + 1$. Two bilateral interbank positions $i : j$ and $k : l$, with associated $|\widehat{\rho}^s|$, are connected (that is, $\widehat{w}_{i:j,k:l} = 1$) if $|\widehat{\rho}^s|\rangle T^{-1/2}\Phi^{-1}\left(1-\frac{p/2}{N-s+1}\right)$; otherwise, they are unconnected ($\widehat{w}_{i:j,k:l} = 0$). Density is the percentage of significant connections, over the total number of possible connections. Data from Superintendency of Banks and Financial Institutions and Central Bank of Chile.

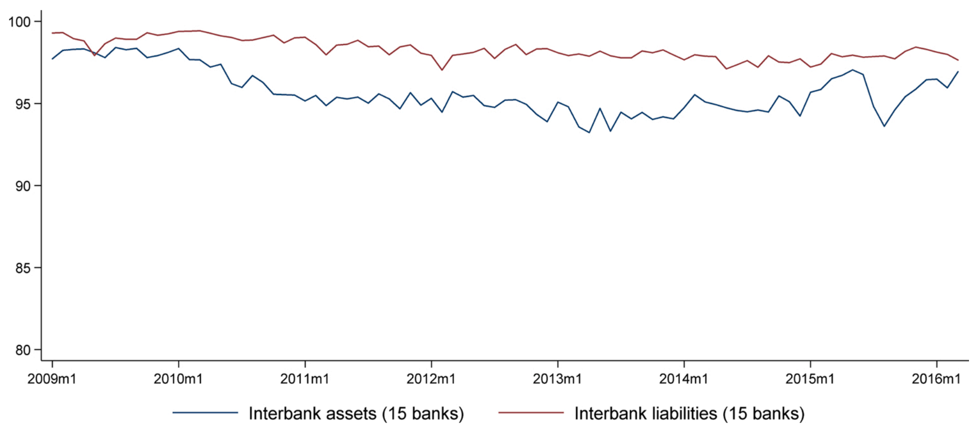

Fig. A1. Evolution of the 15 banks' interbank assets (blue) and liabilities (red), over total interbank assets and liabilities. Period 2009m1–2016m3. *Notes*: The figure depicts the monthly evolution of the 15 banks' interbank assets (blue) and liabilities (red), over total interbank assets and liabilities (23 banks' interbank assets), over the period 2009m1–2016m3. Interbank assets (or liabilities) includes include interbank loans, current accounts, repurchase agreements, derivatives, term deposits, bank bonds, interbank loans with collateral, and operations in the course of liquidation. Data from Superintendency of Banks and Financial Institutions and Central Bank of Chile. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

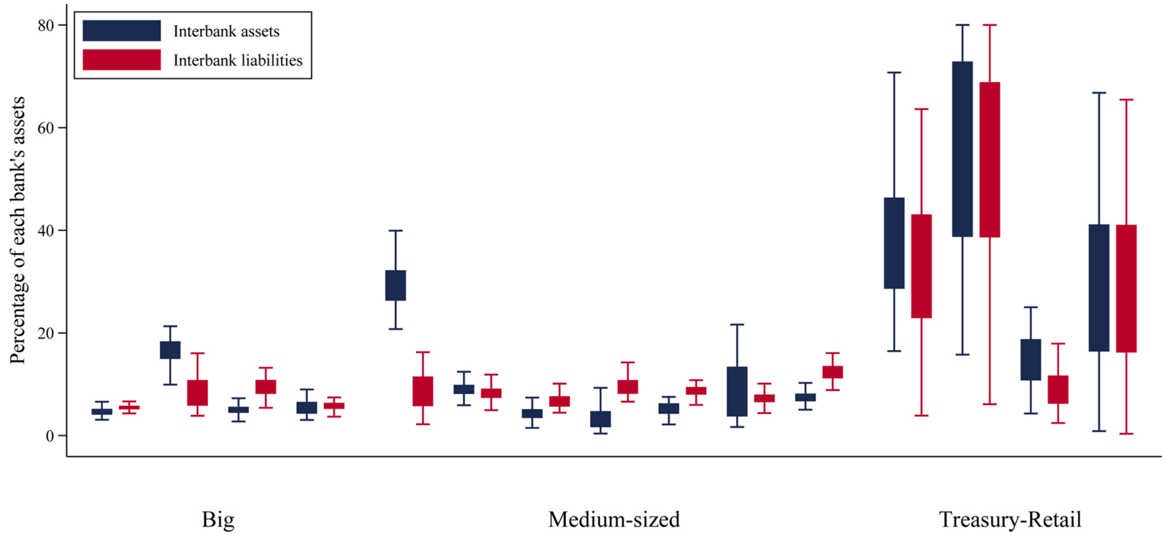

Fig. A2. Distribution of interbank assets and interbank liabilities by bank. *Notes*: This figure shows the distribution of interbank assets and liabilities for each bank in relation to their total assets. In order to preserve anonymity, we group banks into three categories: Big, medium-sized, and treasury-retail, which are mostly oriented to consumer-lending and treasury activities. Boxes show the fifth, twenty-fifth, seventy-fifth, and ninety-fifth percentiles of monthly ratios. Interbank exposures include interbank loans, current accounts, repurchase agreements, derivatives, term deposits, bank bonds, interbank loans with collateral, and operations in the course of liquidation. Data from Superintendency of Banks and Financial Institutions and Central Bank of Chile.

Table A4
Testing for weak cross-sectional dependence in the dataset.

Variables	CD	$\widehat{\overline{\rho}}$	α^{-}
Bilateral interbank positions	78.50	0.06	0.86
Non-performing loans	11.57	0.14	0.84
Return on assets	28.83	0.30	0.94
Foreign liabilities	15.24	0.16	0.84
Bank deposits	45.21	0.47	0.99
Total loans	63.49	0.71	0.99
Capital adequacy ratio	12.09	0.16	0.85
Total assets	68.43	0.72	0.99

Notes: This table reports Pesaran's cross sectional dependence test statistics, hereafter CD; the average pair-wise correlation coefficient, $\overline{\rho}_N$, and the estimated exponents of cross-sectional dependence for the raw data, α^{-}. The null hyphothesis is that the errors in the panel data model are weakly cross-sectionally dependent. $\widehat{\overline{\rho}}$ is the average pair-wise correlation. α^{-} is the exponent of cross-sectional dependence of the raw data, that is, before the de-factoring. Bilateral exposure (millions of Chilean Pesos) includes include interbank loans, current accounts, repurchase agreements, derivatives, term deposits, bank bonds, interbank loans with collateral, and operations in the course of liquidation. Non-performing loans are loans where the borrower is 90 days past due overt total loans. Return on assets corresponds to the return on assets before tax. Foreign liabilities correspond to foreign liabilities (millions of Chilean Pesos). Bank deposits correspond to term deposits owned by individuals, firms, and financial institutions (millions of Chilean Pesos). Total loans correspond to commercial, consume, and other loans (millions of Chilean Pesos). Capital adequacy ratio is the ratio of a bank's capital in relation to its risk weighted assets and current liabilities. Total assets correspond to the total assets (millions of Chilean Pesos). Data from Superintendency of Banks and Financial Institutions and Central Bank of Chile.

cross-sectional dependence below 0.5 indicates weak cross-sectional dependence in the variable of interest.[21]

Table A4 reports Pesaran's cross sectional dependence test statistics, hereafter CD; the average pair-wise correlation coefficient, $\overline{\rho}_N$, and the estimated exponents of cross-sectional dependence for the raw data, α^{-}.

[21] The exponent of cross-sectional dependence, α, measures how fast the average pair-wise correlation among N units, $\overline{\rho}_N$, tends to zero. As shown in Bailey et al. (2016b), values of α in the range $[0, 0.5[$correspond to a weak degree of cross-sectional dependence, with $\overline{\rho}_N$ tending to zero very fast, at an order that ranges from N^{-2} to N^{-1}. In turn, values of α in the range $[0.5, 0.75[$represent moderate degrees of cross-sectional dependence. In this case, $\overline{\rho}_N$ tends to zero at a rate ranging from N^{-1} to $N^{-1/2}$. For values of α in the range $[3/4, 1[$, cross-sectional dependence is strong, with $\overline{\rho}_N$ tending to zero rather slowly. Finally, $\overline{\rho}_N$ converges to a non-zero value only if $\alpha = 1$.

Table A5
Evaluating the success of the de-factoring, with the exponents of the cross-sectional dependence, for several alternative values of *m*.

Variables	Degree of cross-sectional dependence (α)								
	α^-	m = 1		m = 2		m = 3		m = 4	
		α^+	%Var	α^+	%Var	α^+	%Var	α^+	%Var
Bilateral interbank positions	0.86	0.57	0.28	0.57	0.37	0.56	0.43	0.55	0.47
Non-performing loans	0.84	0.36	0.47	0.25	0.70	0.23	0.81	0.21	0.87
Return on assets	0.94	0.68	0.38	0.48	0.69	0.40	0.80	0.39	0.86
Foreign liabilities	0.84	0.80	0.26	0.37	0.49	0.33	0.58	0.33	0.66
Bank deposits	0.99	0.35	0.79	0.35	0.86	0.34	0.90	0.34	0.93
Total loans	0.99	0.27	0.88	0.27	0.94	0.25	0.97	0.23	0.99
Capital adequacy ratio	0.85	0.82	0.36	0.23	0.57	0.23	0.68	0.21	0.78
Total assets	0.99	0.45	0.78	0.38	0.89	0.37	0.95	0.37	0.98

Notes: This shows the de-faactoring of the variables for several alternative values of *m*. We estimate the common factors by principal components analysis; we obtain the de-factored observations as residuals from ordinary least square regressions for each variable of interest on the *m* largest principal components. To select the appropriate *m* for each variable, we consider a grid of *m*, from $m = 1$ to $m = 4$ principal components. We then check the effectiveness of the de-factoring by looking at the exponents of the cross-sectional dependence, associated to each possible value of *m*. Finally, for each variable of interest, we select the minimum *m*, such that $\alpha^+ < 0.5$. For each possible value of *m* and for each variable of interest, this table reports the exponents of cross-sectional dependence, after the defactoring of the observations, α^+. For comparison, it also presents the exponents of cross-sectional dependence before the defactoring, α^-. See Bailey et al. (2016b) for details. *m* is the number of principal components we use in the de-factoring of the observations. %Var is the cumulative proportion of variance explained by the first *m* principal components. Bilateral exposure (millions of Chilean Pesos) includes include interbank loans, current accounts, repurchase agreements, derivatives, term deposits, bank bonds, interbank loans with collateral, and operations in the course of liquidation. Non-performing loans are loans where the borrower is 90 days past due overt total loans. Return on assets corresponds to the return on assets before tax. Foreign liabilities correspond to foreign liabilities (millions of Chilean Pesos). Bank deposits correspond to term deposits owned by individuals, firms, and financial institutions (millions of Chilean Pesos). Total loans correspond to commercial, consume, and other loans (millions of Chilean Pesos). Capital adequacy ratio is the ratio of a bank's capital in relation to its risk weighted assets and current liabilities. Total assets correspond to the total assets (millions of Chilean Pesos). Data from Superintendency of Banks and Financial Institutions and Central Bank of Chile.

Because the cross-sectional dependence test statistics for all the variables are above the critical value of 1.96 at the 5% significance level, we reject the null of weak cross-sectional dependence. We arrive to the same conclusion, when we examine the exponents of cross-sectional dependence α^-, since all the exponents are above the 0.5 threshold. We conclude that there is strong cross-sectional dependence in our dataset. Therefore, we need to model it; we do it by means of a *m*-factor model, as detailed in the next section.

A.3.2 De-factoring observations using principal components analysis

Consider the following *m*-factor model for a given variable $z_{i,t}$ (the bilateral interbank positions or the bank-specific characteristics):

$$z_{i,t} = \gamma' f_t + \xi_{i,t}. \tag{A.1}$$

f_t is the $m \times 1$ vector of (unobserved) common factors (*m* being fixed), γ' is the $N \times m$ or $n \times m$ matrix of factor loadings, for the bilateral interbank positions and the bank-specific characteristics, respectively, and $\xi_{i,t}$ are idiosyncratic errors.

We estimate the common factors by principal components analysis; we obtain the de-factored observations as residuals from ordinary least square regressions for each variable of interest on the *m* largest principal components. To select the appropriate *m* for each variable, we consider a grid of *m*, from $m = 1$ to $m = 4$ principal components. We then check the effectiveness of the de-factoring by looking at the exponents of the cross-sectional dependence, associated to each possible value of *m*. Finally, for each variable of interest, we select the minimum *m*, such that $\alpha^+ < 0.5$.

For each possible value of *m* and for each variable of interest, Table A5 reports the exponents of cross-sectional dependence, after the defactoring of the observations, α^+. For comparison, it also presents the exponents of cross-sectional dependence before the defactoring, α^-.

From Table A5, we choose $m = 4$, in the case of the bilateral interbank positions, whereas we select $m = 1$ for all the bank-specific characteristics, with the exception of Return on assets, for which we set $m = 2$.

A.3.3 Estimating the interbank connection matrix

To identify the non-zero elements of W with those elements of $\widehat{\rho}_{i:j}$ in (2) that are different from zero at a suitable significance level, Bailey et al. (2016a) apply Holm (1979) multiple testing procedure to distinct non-diagonal elements of the sample estimate $\widehat{R} \equiv (\widehat{\rho}_{i:j})$ and show that the non-zeros of $W = (w_{i:j})$ can consistently be estimated by,

$$\widehat{w}_{i:j,k:l} = I\left(|\widehat{\rho}_{i:j,k:l}| \rangle \frac{c_p(N)}{\sqrt{T}}\right), \tag{A.2}$$

with $c_p(N) = \Phi^{-1}\left(1 - \frac{p}{2\times f(N)}\right)$, p is the pre-specified overall size of the test, $\Phi^{-1}()$ is the inverse of the cumulative standard normal distribution and $f(N)$ is such that it increases linearly in N.

After computing the correlation of the de-factored bilateral interbank positions, we set $p = 0.05$ and order $|\hat{\rho}_{i:j,k:l}|$ in a descending manner. Denote the largest value of $|\hat{\rho}_{i:j,k:l}|$ by $|\hat{\rho}^1|$, the second largest by $|\hat{\rho}^2|$ and so on. This way, we obtain the ordered sequence $|\hat{\rho}^s|$ for $s = 1, 2, ..., N^2$. Finally, let $f(N) \equiv N - s + 1$.

Two bilateral interbank positions $i : j$ and $k : l$, with associated $|\hat{\rho}^s|$, are connected (that is, $\hat{w}_{i:j,k:l} = 1$) if $|\hat{\rho}^s|\rangle T^{-1/2}\Phi^{-1}\left(1 - \frac{p/2}{N-s+1}\right)$; otherwise, they are unconnected ($\hat{w}_{i:j,k:l} = 0$). Intuitively, the significance threshold above which a pair of positions are peers of each other becomes stricter along the ordered sequence $|\hat{\rho}^s|$, as it increases with s.

A.4 Expected signs for the banks' specific characteristics

The expected signs of the covariates may differ whether they refer to the lender or the borrower. From the lender perspective, the expected signs for risk and performance are undetermined: On the one hand, banks with more profitable investment projects and/or lower risk may have lower funding costs, which in turn may allow them to lend more in the interbank market. On the other hand, it may be more attractive for a bank which is doing well (high return and/or low risk) to use its liquidity to finance its own investments and therefore lend less in the interbank market.[22]

With regards to the alternative sources of funding variables, the relation between the stock of foreign liabilities and the amount a bank lends in the interbank market is undetermined, because on the one side, a bank borrowing from abroad may be indicating that it does not have excess liquidity to lend in the domestic interbank market. On the other side, the more funding the bank raises, the more funds it has for lending. In the case of the stock of total deposits, we expect a positive relationship with the amount a bank lends in the interbank market. Intuitively, the more deposits the bank receives, the more it can lend.

From the borrower point of view, the relation between risk and performance and the amount banks borrow in the interbank market is an empirical question. This is because on the one hand, riskier or less profitable banks (with a larger proportion of non-performing loans, a lower capital adequacy ratio and/or lower return on assets) may find more difficult to borrow from other banks. On the other side, riskier or less profitable banks may have lower access to international markets and therefore, may want to borrow more from other banks in the domestic interbank market.[23] Concerning the alternative sources of funding observed, we should observe that the more a bank borrows from abroad and/or the larger its stock of deposits, the less it needs to borrow from the domestic interbank market.

Finally, both from the lender and borrower perspective, the expected sign of total loans is ambiguous. This is because the variable total loans indicates to what extent a bank relies more on traditional intermediation activities, as opposed to, for example, more fee and capital income generating trading activities in securities (Liedorp et al., 2010). Its expected sign is hence ambiguous, since an increase in total loans implies more credit risk, but lower market risk.

A.5 Illustrating the interbank connections

To further illustrate the significant interbank connections we have identified when estimating $\widehat{\mathrm{W}}$, we now provide an example with six banks. To this end, Fig. A3 represents a theoretical interbank connection matrix $\widehat{\mathrm{W}}^{\mathrm{H}}$, with colored entries indicating all possible positions that the four identified types of significant interbank connections could take.

To begin with, the red colored entries display all possible pairs of bilateral interbank positions which could be classified as reciprocal. Consider for instance, the entries (1:3,3:1) and (3:1,1:3). If the pair-wise correlation between the bilateral interbank position involving lender bank 1 and borrower bank 3 and the position between lender bank 3 and borrower bank 1 over the sample period were statistically different from zero, a significant and reciprocal interbank connection would occur.

Second, the blue colored entries in $\widehat{\mathrm{W}}^{\mathrm{H}}$ represent all possible pairs of bilateral interbank positions which could be classified as common lender interactions. As an illustration, consider the blue colored entries in column 1:2. They correspond to the entries (1:3,1:2), (1:4,1:2), (1:5,1:2) and (1:6,1:2), which have in common that they are pairs of bilateral interbank positions with bank 1 being the lender bank. As before, if the pair-wise correlation between any of these pairs over the sample period were statistically different from zero, a significant interbank connection to be labelled as a common lender interaction, would occur.

Third, the green colored entries in $\widehat{\mathrm{W}}^{\mathrm{H}}$ identify all possible pairs of positions which we could classify as common borrower interactions. As an example, consider the green colored entries in column 3:2, corresponding to the pairs (1:2,3:2), (4:2,3:2), (5:2,3:2) and (6:2,3:2). They are all pairs of bilateral interbank positions with bank 2 being the borrower bank.

[22] Using data on the Portuguese interbank market, Cocco et al. (2009) find that more profitable banks lend less. In Portugal, banks with better investment opportunities are net borrowers in the interbank market.

[23] Interestingly, using data on the Dutch interbank market from 2008 to 2011, Blasques et al. (2018)show that as a response to larger credit risk, their estimated interbank network shrinks. This is because bilateral interest rates increase; interbank borrowing becomes less attractive, relative to the outside option (given by the central bank's standing facilities) and therefore, some trades are substituted by recourse to the standing facilities.

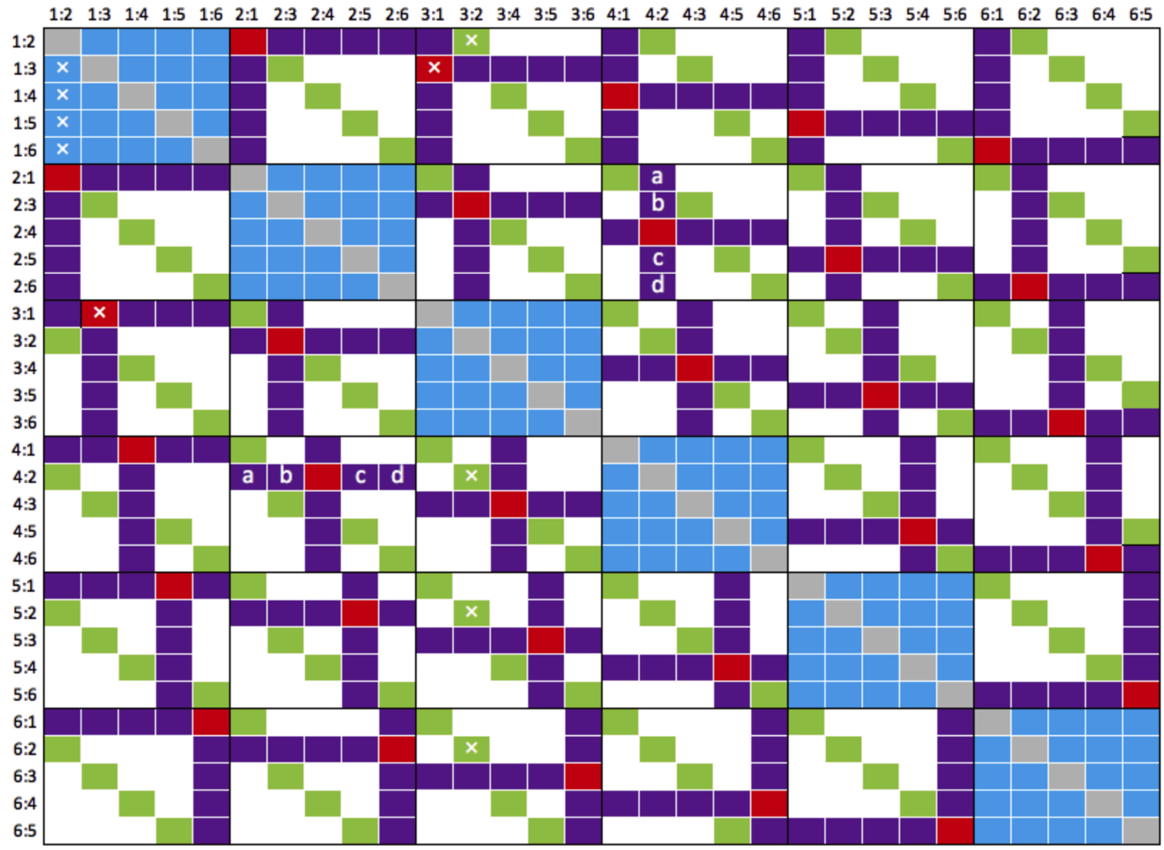

Fig. A3. A theoretical interbank connection matrix $\widehat{W}^H$ illustrating the significant interbank connections types. *Notes*: The figure depicts a hypothetical interbank connection matrix $\widehat{W}^H$, with the aim of illustrating the types of significant interbank connections we have identified when estimating $\widehat{W}$. Red, blue, green and violet colored entries represent the reciprocal, common lender, common borrower and intermediation interaction types, respectively. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

Finally, the violet colored entries in $\widehat{W}^H$ display all possible interbank connections which we could classify as intermediation. For instance, consider the pairs (4:2,2:1), (4:2,2:3), (4:2,2:5) and (4:2,2:6), identified as entries a, b, c and d in $\widehat{W}^H$, respectively. An intermediation interaction type would then occur if, for instance, the pair-wise correlation between the bilateral interbank positions involving lender bank 4 and borrower 2 and lender bank 2 and borrower bank 3 over the sample period were statistically different from zero.

A.6 Model specification with independent observations

Table A6 reports the model estimates of specification (3), assuming $\psi = 0$.

For robustness, we add to the model specification in Table A6 the two dummy variables if there is at least one public bank or one foreign bank in the dyadic. While the estimated coefficients and standard errors barely change, relative to the ones in Table A6, the dummy variables were non-significant. The latter is indicating that the dyadic fixed effects are sufficient to capture the heterogeneity among banks participating the interbank market. As a result, we do not include the indicator variables.

A.7 Robustness checks to the SAR model estimates

We conduct two robustness checks. First, we estimate alternative model specifications to the one in Table 8. Among them, it is worth mentioning that we exclude the capital adequacy ratio; we express non-performing loans, foreign liabilities, bank deposits and total loans, as proportions of banks' total assets; we add the two dummy variables if there is at least one public bank or one foreign bank and finally, we augment the specification in Table 8 with the information on the interest rate that banks pay in the wholesale secondary market.

Second, because we find that size and market focus are important determinants of banks' propensity to interact in the interbank

Table A6
Panel fixed effects, applied to the de-factored lending/borrowing interbank positions.

Variable	Coefficient	*T*-stat	*P*-value
Lender characteristics			
Non-performing loans	**1.29**	2.37	0.02
Return on assets	**1.17**	2.08	0.04
Foreign liabilities	**− 1.24**	− 2.27	0.02
Bank deposits	**1.61**	2.77	0.01
Total loans	**1.37**	2.36	0.02
Capital adequacy ratio	− 0.35	− 0.60	0.55
Borrower characteristics			
Non-performing loans	− 0.56	− 1.03	0.30
Return on assets	**− 1.07**	− 1.89	0.06
Foreign liabilities	**− 1.49**	− 2.72	0.01
Bank deposits	**− 1.41**	− 2.44	0.01
Total loans	**0.78**	1.34	0.18
Capital adequacy ratio	− 0.91	− 1.58	0.11
Observations	18,270		
R^2	0.02		
Number of bilateral interbank positions	210		
Dyadic fixed effects	YES		

Notes: This table exhibits the panel model estimates with dyadic fixed effects, where the dependent variable is the de-factored bilateral lending/borrowing positions in the interbank market (de-factored by means of a four-factor model). All the control variables are de-factored, standardized and lagged one period. Bilateral exposure includes include interbank loans, current accounts, repurchase agreements, derivatives, term deposits, bank bonds, interbank loans with collateral, and operations in the course of liquidation. Non-performing loans are loans where the borrower is 90 days past due overt total loans. Return on assets corresponds to the return on assets before tax. Foreign liabilities correspond to foreign liabilities. Bank deposits correspond to term deposits owned by individuals, firms, and financial institutions. Total loans correspond to commercial, consume, and other loans. Capital adequacy ratio is the ratio of a bank's capital in relation to its risk weighted assets and current liabilities. Total assets correspond to the total assets. In bold: Significant coefficient estimates at 10% significance level. *T*-stat stands for the test statistic *t* and *P*-value stands for probability value. Data for January 2009 to March 2016. Data from Superintendency of Banks and Financial Institutions and Central Bank of Chile.

market, we use this information to construct alternative weight matrices. More specifically, for size, we consider the information on banks' assets, whereas in the case of market focus, we rely on Jara and Oda (2015)'s bank categories, namely, big and medium-sized standard commercial banks, retail and treasury banks.[24]

In relation to the first robustness check, we conclude that the results we highlight from Table 8 continue to be valid, with the spatial autoregressive parameter estimates ranging between 0.20 and 0.40. In particular, when including the interest rate that banks pay in the wholesale secondary market as an additional explanatory variable, we find, as expected, that banks prefer to lend in (rise funding from) the interbank market, when the interest rate in the wholesale secondary market increases.

Concerning the second robustness check, we observe that the signs of the model estimates relying on the alternative weight matrices tend to coincide with those reported in Table 8. Furthermore, the spatial autoregressive parameter estimates now range between 0.10 and 0.20.

Appendix B. Supplementary data

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.ribaf.2021.101438.

[24] In the case of assets, we follow the same weight matrix estimation procedure than for the interbank connection matrix: We test the assumption of weak cross-sectional dependence and since we reject the null, we model the implied strong cross-sectional dependence, by means of a *m*-factor model. Next, we apply the Holm multiple testing procedure to find the positive elements of this alternative weight matrix, which we finally normalise. Regarding the weight matrix based on banks' classification, which we denote as $\mathrm{W}^{\mathrm{Types}}$, we create a lender-based weight matrix as $\mathrm{W}^{\mathrm{Types}} = \mathrm{W}^{\mathrm{types}} \otimes \mathrm{I}_n$, with $\mathrm{W}^{\mathrm{types}}$ the $n \times n$ weight matrix formed with the banks' categories in Jara and Oda (2015). More specifically, element $w_{i;j}^{\mathrm{types}} = 1$ if banks *i* and *j* belong to the same category; otherwise, $w_{i;j}^{\mathrm{types}} = 0$. We then normalise the weight matrix. It is worth mentioning that the lender-based centric ordering is without loss of generality, since results are not sensitive to the ordering.

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