Measuring endogenous peer effects in interbank markets

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Abstract

In this paper, we propose a flexible methodology to identify and quantify the importance of endogenous peer effects, which in this work means the possibility that other banks' lending and borrowing choices in the interbank market affect (in an economically relevant way) the lending/borrowing position of two specific banks. Two nice features of our approach are that it identifies different types of interactions between banks and that it allows for varying degrees of intensity of these peer effects. We have access to a unique dataset since it includes all interbank loans that have taken place in the Chilean interbank market between 2009 and 2016. We find that there is considerable heterogeneity across banks in their degree of sensitivity to other banks' choices in the interbank market, with treasury banks and small banks being the most sensitive. We provide some possible explanations for these various sensitivities.

Keywords: Endogenous peer effects, financial interconnections, interbank market, heterogeneous spatial autoregressive model.

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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 over the recent past (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 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). Furthermore, measuring the extent to which financial institutions' decisions are related to each other is crucial for understanding the risk exposure of the system as a whole where shocks to some of its parts can develop into a wider breakdown of banks and financial institutions through cascades of insolvencies and domino effects (Gai *et al.*, 2011).

In this paper, our interest is on financial interconnections arising from banks' cross-exposures in the interbank market and on the extent to which these interconnections affect banks' choices in the interbank market. Specifically, the paper has two objectives: The first one is to determine whether and in which manner(s) banks financially connect in the interbank market. For the latter, we structure banks' cross-exposures in the form of a financial network and examine, for each pair of cross-exposures, whether there is a statistically significant correlation between them. If it is the case, we consider that there is an interbank connection between the two given bilateral interbank positions and that they are peers of each other. The second objective is to determine causality, namely, to determine whether and how peers (the interbank connections we identify in the first step) affect the lending/borrowing choices of any two specific banks. To achieve these two objectives, we propose a flexible methodology that allows for different types of interactions between banks. In addition, our methodology enables us to extract some conclusions on the mechanisms through which these peer effects might operate. Our case of application is the Chilean interbank market.

The reasons for peer effects in interbank markets can be various. For instance, a bank may be unsure about its optimal risk management policy and may choose to free ride its peers' information acquisitions and follow their (lending/borrowing) decisions (Banerjee, 1992). Or, banks may put more weight on its peers' choices in the interbank market than on its own information, if those other banks are perceived as having greater expertise (Bikhchandani *et al.*, 1998). Alternatively, banks may find optimal to mimic each other and invest in the same type of assets, in the expectation of collective bailouts (Acharya and Yorulmazer, 2007; Ratnovski, 2009; Farhi and Tirole, 2012). An additional possible reason, among others, is that banks are sensitive to the decisions of their peers, with which they have long-term lending relations (Cocco *et al.*, 2009), with these relations being some form of cross-insurance between them (Blasques *et al.*, 2018).

However, identifying the causal effect of peers is empirically challenging. One key challenge is to determine what drives the correlation between outcomes of individuals, in our case banks, which interact together in the interbank market. In a pioneer study, Manski (1993) distinguishes between exogenous or contextual effects (which in our context refers to the influence of exogenous characteristics that both a bank and the banks in its peer group share), endogenous effects (namely, how a bank's choice in the interbank market is affected by the behavior of its 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 peer effects from correlated effects.

Concerning the first concern, we follow the identification strategy of Bramoullé *et al.* (2009) and De Giorgi *et al.* (2010), who show, independently, that there is identification if agents or units belong to different, not fully-overlapping groups. In our study, a crucial definition which helps us counter the first identification concern is the unit of analysis. Our unit of analysis is the lending/borrowing position between any two banks in the interbank market. Since each unit can be correlated with more than one other unit, which is equivalent to say that the peer groups are specific to each bilateral interbank position, the condition of belonging to non-overlapping groups is fulfilled; therefore, peer effects can be identified. In regards to the second identification concern, because we find evidence of strong cross-sectional dependence in our dataset, we model these unobserved common factors by means of factor models. We then take them out, yielding the de-factored observations, as residuals from ordinary least square regressions of each bilateral interbank position on some principal components.

In relation to the distinction between the endogenous and the contextual peer effects, in this paper, we focus on the endogenous peer effects and assume that there are no contextual effects. The motivation for such an assumption is precisely our unit of analysis: Since the unit is not a bank, but a lending/borrowing position between two banks, we believe it is sufficient to control for the lender and borrower banks' characteristics (as well as the common factors), when determining the causal effect of peers in the interbank market (Norton *et al.*, 1998; Trogdon *et al.*, 2008; Gaviria and Raphael, 2001; Powell *et al.*, 2005, are other applications assuming that there are no contextual effects). Supporting this assumption, we conduct a Bayesian model comparison test (Hepple, 2004; LeSage, 2014) which favors the simplest model, that is, excluding the contextual effects.

Specifically, to characterize the way(s) banks financially connect in the interbank market, we start by estimating an interbank connection matrix: Each entry in this symmetric matrix corresponds to a pair of bilateral interbank positions and represents the interaction, if any, between the positions. We say that two bilateral interbank positions are significantly connected and are peers of each other, if the sample estimate of the pair-wise correlation of the two positions over the time frame is statistically different from zero; otherwise, they are unconnected.

To identify the causal effect of interbank connections on a given bilateral interbank position, we apply results from the spatial econometrics literature; in particular, we follow closely Bailey *et al.* (2016a)'s two-stage estimation and inference methodology. Precisely, we treat the estimated interbank connection matrix as a weight matrix, and estimate a heterogenous spatial autoregressive model or HSAR, that measures the influence, if any, of these peer effects: The model relates the bilateral interbank positions with the (lagged) lender and borrower-specific balance sheet characteristics, as well as heterogeneous spatial autoregressive parameters (one parameter for each bilateral interbank position), measuring the strength to which banks' lending/borrowing choices in the interbank market are influenced by each other.[1] The estimation method is a quasi-maximum likelihood procedure, which accounts for the endogeneity of the interbank connection matrix.[2] An additional advantage of the HSAR is that it allows us to extract some conclusions on the channels through which the endogenous peer effects might operate.

We combine information from two datasets, whose source is the Chilean Superintendency of Banks and Financial Institutions. To begin with, 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. We add these instruments up to come up with the monthly average evolution of the total bilateral positions in the interbank market.

The second dataset provides monthly information on banks' balance sheet characteristics. More specifically, it includes monthly return on assets; the proportion of non-performing loans for a

[1] Since we find evidence of strong cross-sectional dependence both in the dependent and in the independent variables, we use the de-factored observations not only to estimate the interbank connection matrix, but also to estimate the spatial autoregressive model.

[2] For comparison, we also estimate a panel regression model and a single spatial autoregressive model or SAR model. While both the panel regression and the SAR models relate bilateral interbank positions with the (lagged) lender and borrower-specific balance sheet characteristics, the difference between the two is that the former supposes independence between banks participating in the Chilean interbank market, whereas the latter assumes a single spatial autoregressive parameter measuring the strength of the peer effects.

period exceeding 90 days, over the total outstanding credit granted by the bank; the stock of foreign liabilities and bank deposits, with the latter including deposits from institutional investors, firms and retail depositors; the sum of mortgage, commercial and consumer loans and the capital adequacy ratio, which is the ratio of a bank's capital to its risk weighted assets. For robustness, we also consider banks' assets; type of property, namely, whether the bank is public (owned by the state) or private; banks' nationality, that is, whether it is a domestic or a foreign bank and the interest rate that each bank bears in the wholesale secondary market.

The time frame goes from January 2009 to March 2016. We consider a set of 15 domestic and foreign banks, actively participating in the interbank market over the period, and representing more than 95% of the Chilean interbank market. The 15 banks result in 210 (15×14) distinct bilateral interbank positions. 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 network literature, which typically approximates individual exposures from aggregates through algorithms.

One could question the appropriateness of having a single interbank connection matrix, when we observe the evolution of the bilateral interbank positions. The reason for that is that 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. On top of that, 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 registering stable market shares.

From the estimation of the interbank connection matrix, we find that two types of (statistically significant) interbank connections dominate, namely, the symmetric and the common lender. A symmetric interaction occurs when the pair of bilateral interbank positions involves only two distinct banks, say bank i and j, such that bank i lending to bank j appears to be significantly connected to bank j lending to bank i. In turn, there is a common lender interaction type, when the pair of bilateral interbank positions have both positions with the same lender bank. Specifically, bank i lending to bank j is significantly connected with bank i lending to another bank l (distinct from bank j). Both interaction types account for more than 90% of the total number of interbank connections we identify.

In addition, we observe the common borrower (which requires that the pair of bilateral interbank positions involved have both positions with the same borrower bank) and the intermediation interaction type (bank i lending to bank j significantly connected with bank j lending to bank l defines an intermediation interaction, with bank j being the intermediary bank). Both the common borrower and the intermediation interaction types represent each 3% of the total number of interbank connections. Also, the four previously characterized interbank connection types are due to significantly positive pairwise correlations

Focusing on the symmetric interactions, we find that treasury banks (that is, banks which are subsidiaries of foreign banks, whose core activity is to provide investment banking services; Jara and Cabezas, 2017), have the largest number of symmetric interactions. For the latter, we classify the bilateral interbank positions in our dataset into the four identified interbank connections and then examine the banks present in the distinct bilateral interbank positions being part of each connection type. In addition, we document that in the bilateral interbank positions which we classify as being part of the symmetric connection type, treasury banks tend to lend to and borrow from a smaller number of counterparties, which is consistent with these banks having lending/borrowing relations. On top of that, the HSAR model estimates reveals that 60% of the bilateral interbank positions which we classify as belonging to the symmetric interaction type exhibits significant spatial autoregressive parameter estimates. It thus supports the interpretation that these banks are likely to be sensitive to the lending/borrowing choices of the banks with which they have relations.

Regarding the common lender interactions, we observe that with one exception, all banks in the bilateral interbank positions classified as common lender interactions are commercial banks (participating in all market segments), with the majority of them (four out of six) being small or medium-sized institutions. Furthermore, we find that, on average, the lender banks in the common lender interaction type make more money when lending to the banks with which they are significantly connected, relative to the average returns they obtain when lending to other banks, with the mean differences being statistically significant.

There are two possible explanations for the common lender interactions. The first one is that these interactions are simply reflecting that the lenders involved are diversifying their portfolios by lending to the borrowers concerned. According to this view, lenders look at potential borrowers' characteristics to decide whether and by how much to lend, whereas borrower banks would have a more passive role, posting their liquidity needs (for instance, in an auction) to any bank willing to lend to them. Therefore, this explanation would not be a peer effect story. The second possible interpretation is a peer effect explanation. Although we cannot formally test these two alternative explanations, the HSAR model estimates reveal that 39% of the bilateral interbank positions which we classify as belonging to the common lender interaction type exhibits statistically significant spatial autoregressive parameter estimates. It thus provides some support to the second interpretation. Conditional on the second interpretation for the common lender interactions playing some role, we now examine the direction in which these peer effects might operate.

Manski (2000) identifies three channels through which an action chosen by one agent (in our case, a lending/borrowing decision between two banks in the interbank market) may affect the actions of other agents (other cross-exposures in the same market): Constraints, expectations, and preferences. In our context, constraint interactions between borrower banks j and l both borrowing from bank i, could occur if the amount bank i can lend to j is limited, at least in some way, by the amount bank i lends to l. Suppose, for instance, that as part of bank i's credit risk management policy, bank i decides to lend to bank j up to a certain level, above which it prefers to lend to another bank, like bank l. However, if this substitution effect between banks j and l were at play, we should observe statistically significant negative pairwise correlations. On the contrary, all the common lender connections are due to statistically significant positive pairwise correlations. Therefore, we believe that the constraint interaction channel is unlikely to play a role in this case.

In turn, the expectation channel for the common lender connections would be, when determining which bank(s) to ask for funding, borrower bank j (or bank l) finds informative that bank l (bank j) borrows from bank i and then chooses to follow it by borrowing from the same bank i. Last, the preference channel would be that borrower bank j (or l)'s preference for asking for funds to bank i is influenced by the fact and/or the amount that borrower bank l (or j) borrows from the same bank i. Unfortunately, the evidence we have does not allow to disentangle between the expectation nor the preference channel for the endogenous peer effects.[3]

The HSAR model estimates also reveal that there is considerable heterogeneity across banks in their degree of sensitivity to other banks' choices in the interbank market. As a matter of fact, only a third of the bilateral interbank positions exhibit statistically significant spatial autoregressive parameter estimates. The other side of the coin is that the mean and median of the significant spatial autoregressive parameter estimates are both 0.7, closed to the maximum possible value, which is 1. Both aspects hence reinforce the relevance of having a methodology that allows for different degrees of intensity of the peer effects.

Finally, looking at the bank characteristics which could make banks more likely to be sensitive to the lending/borrowing choices of other banks in the interbank market, the HSAR model estimates

[3]Some anecdotal evidence indicates that interbank loans in Chile are traded both in auctions and over-the-counter (which would be consistent with the expectation and/or the preference channels being at place on the borrower side), with the importance of the latter segment being non-negligible. However, we do not observe the amount of interbank loans traded in each segment, which could help us say something about the plausibility of the channels.

show that small (with assets belonging to the first quartile of the empirical distribution of banks' assets) and treasury borrower banks are the most sensitive to the influence of other banks' choices in the Chilean interbank market. 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.

Wrapping up, from a methodological standpoint, we contribute to the existing literature, by proposing a methodology which offers the necessary flexibility to allow for different degrees of intensity of the peer effects and for various types of interbank connections. In fact, the literature typically assumes a single parameter to measure the influence of peer effects (for instance, Liedorp et al., 2010; Craig et al., 2014 and Silva, 2019). On top of that, our results demonstrate that whether and to what extent peer effects matter depend on the banks under analysis: Different types of banks appear to be more or less sensitive to other banks' choices in the interbank market. In this paper, we suggest some possible reasons for these various sensitivities.

Finally, from a policy standpoint, since we find that the influence of peer effects is not homogenous across banks, we conclude that the ability of a shock to one bank or group of banks to spread to other banks through the interbank market depends on the bank(s) affected. In our words, the larger the number of significant interbank connections that the bank(s) hit by a negative shock has (have), the more likely it is that peer effects amplify counterparty risk through the interbank market.

The remainder of the paper is organized as follows. Section 2 describes the methodology we use to identify, measure and quantify the importance of endogenous peer effects. Section 3, in turn, presents the data and some descriptive statistics, while section 4 exhibits the empirical results and discusses the main findings of the paper. Finally, section 5 concludes. The appendix contains additional descriptive statistics, absent in the main text.

1.1 Literature Review

First, our paper contributes 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) and banks' risk management policies (Liedorp *et al.*, 2010; Craig *et al.*, 2014; Tonzer, 2015), among other domains. Typically, the identification of peers is geographic.

Relying on the same bank-specific characteristics that this literature considers, we share with it the conclusion that peer effects matter, in our case, to explain banks' lending/borrowing choices in the Chilean interbank market. We contribute to it, in two dimensions: On one hand, because instead of using a geographic or business type definition of peers, we identify peers statistically. On the other hand, we add to it by showing that it is important to allow for heterogeneity when studying the determinants of banks' decisions in the interbank market.

Second, this paper relates to the literature that addresses the issue of identification of peers by non-zero elements of an assumed sparse covariance matrix. A number of estimation approaches exist for the estimation of the covariance matrix, namely, generalized vector-autoregressive models or lasso-type penalties (Diebold and Yilmaz, 2012, 2014; Demirer *et al.*, 2017; Manresa, 2015).

We add to this literature, by applying an alternative methodology to identify the peers, that is, a multiple-testing procedure. The special feature of the procedure is that it requires a stricter significance threshold for the comparison of any pair of bilateral interbank positions, relative to a simple testing procedure. We then evaluate our approach in two steps: First, by exploring the type of interactions that our methodology delivers; second, by determining whether the parameters measuring the influence of peer effects contribute to explain the amount banks participate in the interbank market.

From a methodological standpoint, we follow Bailey *et al.* (2016a): We apply their two-step spatio-temporal methodology to determine, first, the significant interbank connections and second, to obtain consistent estimates of the heterogenous spatial autoregressive model. From an applied point of view, we are close 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 modeling banks' lending/borrowing choices in the interbank market.

2 Methodology

Section 3 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 homogenous and heterogenous spatial autoregressive models.

2.1 Modeling interbank connectedness

At any time period t (with $t = 1, ..., T$), let $\mathbf{Y}_t$ 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 :

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

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 flow matrix (1) in two ways: A lender-centric ordering or a borrower-centric ordering. Denote $\mathbf{y}_t$ the $N \times 1$ vector of bilateral interbank positions. A lender-centric ordering requires $\mathbf{y}_t^l = vec(\mathbf{Y}_t)$, whereas a borrower-centric ordering needs $\mathbf{y}_t^b = vec(\mathbf{Y}_t')$.

Without loss of generality, hereafter, we focus on the lender-centric ordering, hence $\mathbf{y}_t = \mathbf{y}_t^l$, with the first n rows of $\mathbf{y}_t$ 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 $\mathbf{y}_t$ 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 $i = 1, .., n$ and $j = 1, .., n$.

Let $\mathbf{W}$ 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. More precisely, an element $w_{i:j,k:l}$ of $\mathbf{W}$ 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 $i, j, k, l \in 1, ..., n$) and zero otherwise, $w_{i:j,k:l} = 0$. By convention, $w_{i:j,i:j} = 0$.

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

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

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

Following Bailey *et al.* (2016a), we then identify the non-zero elements of $\mathbf{W}$ with those elements of $\hat{\rho}_{i:j}$ 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, $\hat{w}_{i:j,k:l}=1$) 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 ($\hat{w}_{i:j,k:l}=0$). Note that the procedure requires that the time dimension be sufficiently large. Appendix A.3 provides technical details on the procedure we follow for determining the significant interbank connections.

There is one technical point to comment, which is that before computing the pair-wise correlations $\hat{\rho}_{i:j,k:l}$, 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 details the procedure we follow for testing the weak cross-sectional dependence assumption and for de-factoring the observations.

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

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 $\mathbf{X}_t$ 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, $\mathbf{y}_t$, we need to repeat $\mathbf{X}_t$ n times to create an $N \times k$ matrix, that we label $\mathbf{X}_{b,t}$, which contains the characteristics of the borrower banks at period t. Hence, $\mathbf{X}_{b,t} = \mathbf{i}_n \otimes \mathbf{X}_t$, with $\mathbf{i}_n$ an $n \times 1$ unit vector and $\otimes$ the Kronecker product. Similarly, we define the $N \times k$ matrix of lender-specific characteristics as $\mathbf{X}_{l,t} = \mathbf{X}_t \otimes \mathbf{i}_n$.[4]

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

$$\mathbf{y_t} = \alpha \mathbf{i_N} + \psi \hat{\mathbf{W}} \mathbf{y_t} + \mathbf{X_l} \beta_l + \mathbf{X_b} \beta_b + \epsilon_\mathbf{t}, \tag{3}$$

with $\alpha \mathbf{i_N}$ 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 $\epsilon_\mathbf{t}$, the residuals, such that $var(\epsilon_\mathbf{t}) = \sigma^2_\epsilon$. For estimation, we rely on Maximum Likelihood (ML) estimation procedures, based on the technical results in LeSage and Pace (2009).[5]

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

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

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

the previous two aspects,

$$\mathbf{y_t} = \alpha \mathbf{i_N} + \Psi \hat{\mathbf{W}} \mathbf{y_t} + \mathbf{B_l} \mathbf{X_{l,t}} + \mathbf{B_b} \mathbf{X_{b,t}} + \mathbf{u_t}, \tag{4}$$

with $\mathbf{\Psi} = diag(\psi)$, $\psi = (\psi_1, \psi_1, ..., \psi_N)'$, $\mathbf{B_l} = diag(\beta'_{1l}, \beta'_{2l}, ..., \beta'_{Nl})$, $\mathbf{B_b} = diag(\beta'_{1b}, \beta'_{2b}, ..., \beta'_{Nb})$, $\beta_{\mathbf{il}} = (\beta_{il_1}, \beta_{il_2}, ..., \beta_{il_k})'$, $\beta_{\mathbf{jb}} = (\beta_{jb_1}, \beta_{jb_2}, ..., \beta_{jb_k})'$ and $\mathbf{u_t}$ the $N \times 1$ vector of error terms, such that $u_{ij,t} \sim IIDN(0, \sigma^2_{u_{ij}})$.[6] For consistent estimation of the parameters, we adapt the Quasi Maximum Likelihood (QML) procedure of Aquaro *et al.* (2015).[7]

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 the 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, by examining the significance and magnitude of the heterogeneous spatial parameter estimates, we obtain evidence in favor or against the three alternative channels of endogenous peer effects, namely, the social learning, the social utility and the borrowing/lending relations motives.

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).

3 The data

Section 4 presents the data and some descriptive statistics.

We combine information from two datasets, whose source is the Superintendency of Banks

[6]For the normalization, we follow LeSage and Chih (2018) and do a doubly-stochastic normalisation (according to which, the row and column sums of $\hat{\mathbf{W}}$ 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).

[7]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.

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 being liquidated), bank bonds, overnight loans without collateral, current accounts, repurchase agreements and overnight loans with collateral. We add them up to come up with the monthly average evolution of the total bilateral positions in the interbank market.

The time frame goes from January 2009 to March 2016. We consider a set of 15 domestic and foreign banks, actively participating in the interbank market over the period.[8] The sample thus comprises 18,270 observations (15 banks over 87 periods, yielding $15 \times 14 \times 87$). 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 network literature, which typically has to approximate individual exposures from aggregates through algorithms.

Figure A1, in the appendix, depicts the monthly evolution of some of the 210 bilateral interbank positions (standardized to have a mean of zero and a standard deviation of one), over the period, whereas figure A2, also in the appendix, plots the distribution of the interbank assets and interbank liabilities for each bank, over each bank's total assets. In addition, figure A3 depicts the evolution of the 15 banks' interbank assets and liabilities over total interbank assets and liabilities.

The second dataset provides monthly information on the banks' balance sheet characteristics. Given equations 3 and 4, we consider the same set of characteristics for the lender and the borrower banks. Specifically, we consider variables related to banks' risk and performance, access to alternative sources of funding and scale covariates.

Regarding the variables that control for 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

[8] To avoid having too many zero value observations, we need to consider a subset of 15 (out of 24) banks participating in the Chilean interbank market, which satisfy the requirements that they participate for at least three years between 2009 and 2016 and that they have less than 40% of zero values in the bilateral interbank positions, over the time frame. We define the percentage of zero values as the fraction between the number of times there is no bilateral interbank transaction over the total number of periods. Importantly, the requirements of 3 years and less than 40% of zero values are without loss of generality, since, on one hand, the 15 banks represent more than 95% of the Chilean interbank market. On the other hand, the to-be presented estimation results are not sensitive to these thresholds. See LeSage and Pace (2009) for a discussion on the zero value problem in spatial interaction models.

ratio thus indicates a less risky bank.[9] To account for the availability of other sources of funding, we control for 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 in our model specifications (equations 3 and 4) 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 add the information on banks' assets; type of property, namely, whether the bank is public (owned by the state) 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 bears in the wholesale secondary 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; this is why we only use it as a robustness check.

Table 1 presents the descriptive statistics of the banks' balance sheet characteristics.

[9]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: Descriptive statistics.

Variables	Obs	Mean	Median	Std Err	Max	Min
Non-performing loans	18,270	0.78	0.68	0.62	3.82	0
Return on assets	18,270	1.22	1.10	1.00	8.35	-1.16
Foreign liabilities	18,270	436	231	496	2099	0
Bank deposits	18,270	3240	2060	3094	11849	0
Total loans	18,270	6033	3769	6459	25325	0
Capital adequacy ratio	18,270	23	13	28	240	9.16
Total assets	18,270	8245	5033	8528	33726	108

Notes: This table reports the descriptive statistics of banks' balance sheet characteristics. Obs and Std Err stand for observations and standard errors, respectively. Data from January 2009 to March 2016. The covariate total loans includes mortgage, commercial and consumer loans. **Data source:** Superintendency of Banks and Financial Institutions and Central Bank of Chile.

From tables 1, together with figures A1, A2 and A3, it is possible to derive the following observations. First, the interbank assets and liabilities of the 15 banks we consider represent 96% and 98% of the total interbank assets and liabilities, respectively. Furthermore, these proportions have been stable over the time frame (see figure A3).

Second, figure A2 shows that there is considerable heterogeneity among banks participating in the interbank market, with some being net lenders, some others being net borrowers and some others being major lenders and borrowers at the same time. More generally, it is worth mentioning that the Chilean banking system, as a whole, presents a high degree of heterogeneity, in terms of size, business orientation and funding structure (Jara and Cabezas, 2017).

Traditionally, banks in Chile are classified into four different categories, that is, big and medium-sized commercial banks, retail and treasury banks (Jara and Oda, 2015). 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 in size and focused on households' finance (consumer and mortgage loans). 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).

In addition to the differences in size, market focus and ownership structure, Chilean banks differ in terms of their degree of international exposure: While treasury banks hold the highest relative level of assets and liabilities overseas, the international activity of retail banks is almost negligible. We will further explore this aspect of heterogeneity, when presenting the estimation results.

4 Results

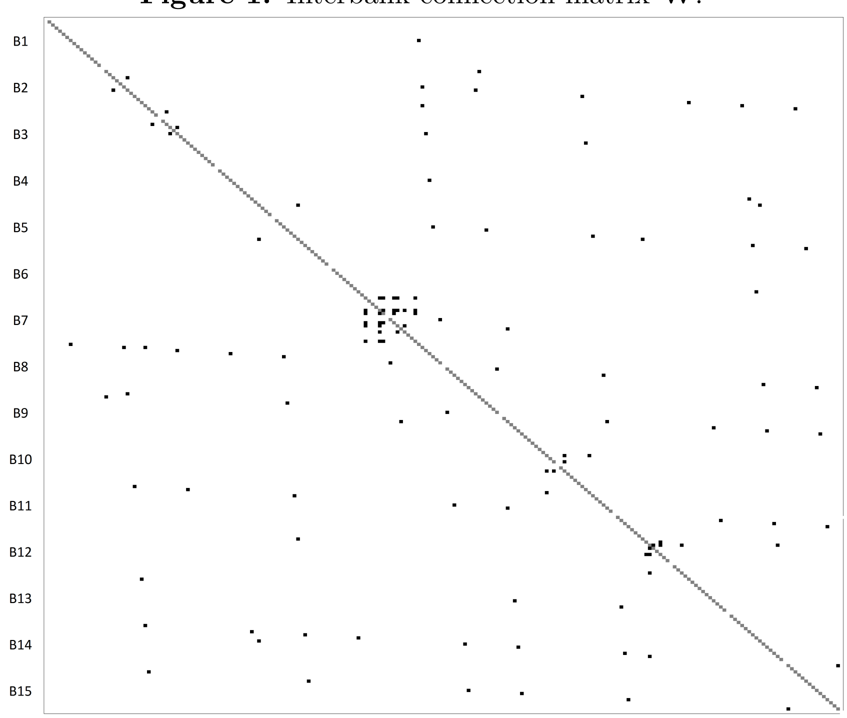
Section 5 starts by presenting the interbank connection matrix, which results from applying the methodology described in section 2.1. Second, it shows the spatial autoregressive model estimates, first, assuming a single and then, heterogenous spatial autoregressive parameters. Section A.5, in the appendix, reports the estimation results, supposing independent observations.

4.1 Estimation of the interbank connection matrix

This section starts by depicting the estimated interbank connection matrix $\widehat{\mathbf{W}}$. Second, by examining the significant interbank connections in $\widehat{\mathbf{W}}$, we characterize the way banks interact in the interbank market. It is important to stress that the interbank connections that we identify with this methodology reflect long-run interactions, since we obtain them from the sample estimates of the pair-wise correlation of any two bilateral interbank positions, over the whole period.

According to our methodology, if two bilateral interbank positions $i:j$ and $k:l$ are significantly connected, we should observe a positive value in the corresponding entry of $\widehat{\mathbf{W}}$. Figure 1 depicts the estimated interbank connection matrix, with black colored entries representing the non-zero elements. To better display the significant interbank connections, we order the rows and columns of the matrix by lender bank. Table A1, in the appendix, reports some additional metrics of $\widehat{\mathbf{W}}$.

Figure 1: Interbank connection matrix $\widehat{\mathbf{W}}$.



Notes: The figure depicts the interbank connection matrix $\widehat{\mathbf{W}}$, based on the significant pairwise correlations of the bilateral interbank positions, according to the Holm procedure. Dimension of the matrix 15×15. B.1 to B.15 stand for banks 1 to 15.

From figure 1 and table A1, there are three elements to highlight. To begin with, $\widehat{\mathbf{W}}$ is a symmetric and sparse matrix. In fact, the degree of sparseness of $\widehat{\mathbf{W}}$, as measured by the proportion of non-zero elements (excluding the diagonal elements) on the total number of entries, amounts to 0.27% ($\frac{120}{210 \times 209}$, with 120 being the total number of non-zero elements). Having a sparse interbank connection matrix has the advantage that it enables to reduce the computational time and memory required for the estimation of the to-be presented spatial autoregressive models.

Second, the share of the bilateral interbank positions without statistically significant connections over the total number of bilateral interbank positions is 58%, with the mean of the significant interbank connections being 0.57. This is indicating, on one side, that more than half of the banks' lending/borrowing choices in the Chilean interbank market have no peers; on the other side, it implies that on average, a bilateral interbank position is connected with less than one different position, with the maximum being six (table A1). 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).

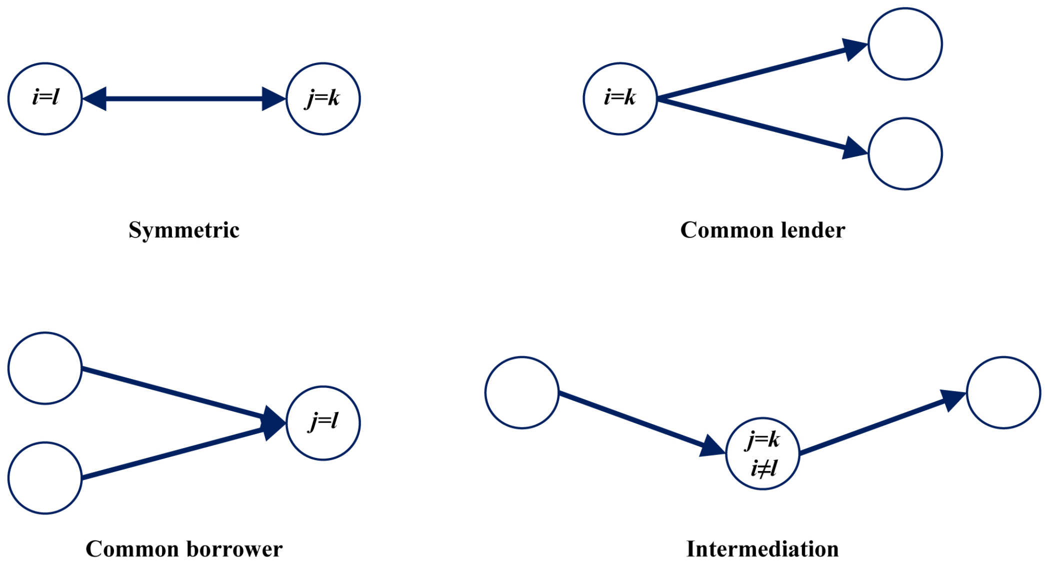
Finally, the great majority of the statistically significant interbank connections are due to significantly positive pairwise correlations. Indeed, 58 out of the 60 distinct significant interbank connections arise from significantly positive pairwise correlations. The latter is thus showing that in most 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 $\widehat{\mathbf{W}}$ 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. Interestingly, from the examination of the $\widehat{\mathbf{W}}$, we identify four types of significantly positive interbank connections.

First, we identify the symmetric 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 symmetric 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.[10] Figure 2 depicts the significant interbank connection types we have identified.

Figure 2: Types of significantly positive interbank connections.



Notes: The figure illustrates the significantly positive interbank connections we have identified when estimating $\widehat{\mathbf{W}}$. The bubbles contain the conditions on $\widehat{w}_{i:j,k:l}$ for each type to hold.

To further illustrate the significant interbank connections we have identified when estimating $\widehat{\mathbf{W}}$, we provide an example with six banks. To this end, figure 3 represents a theoretical interbank connection matrix $\widehat{\mathbf{W}}^{\mathbf{H}}$, 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 symmetric. 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 symmetric interbank connection would occur.

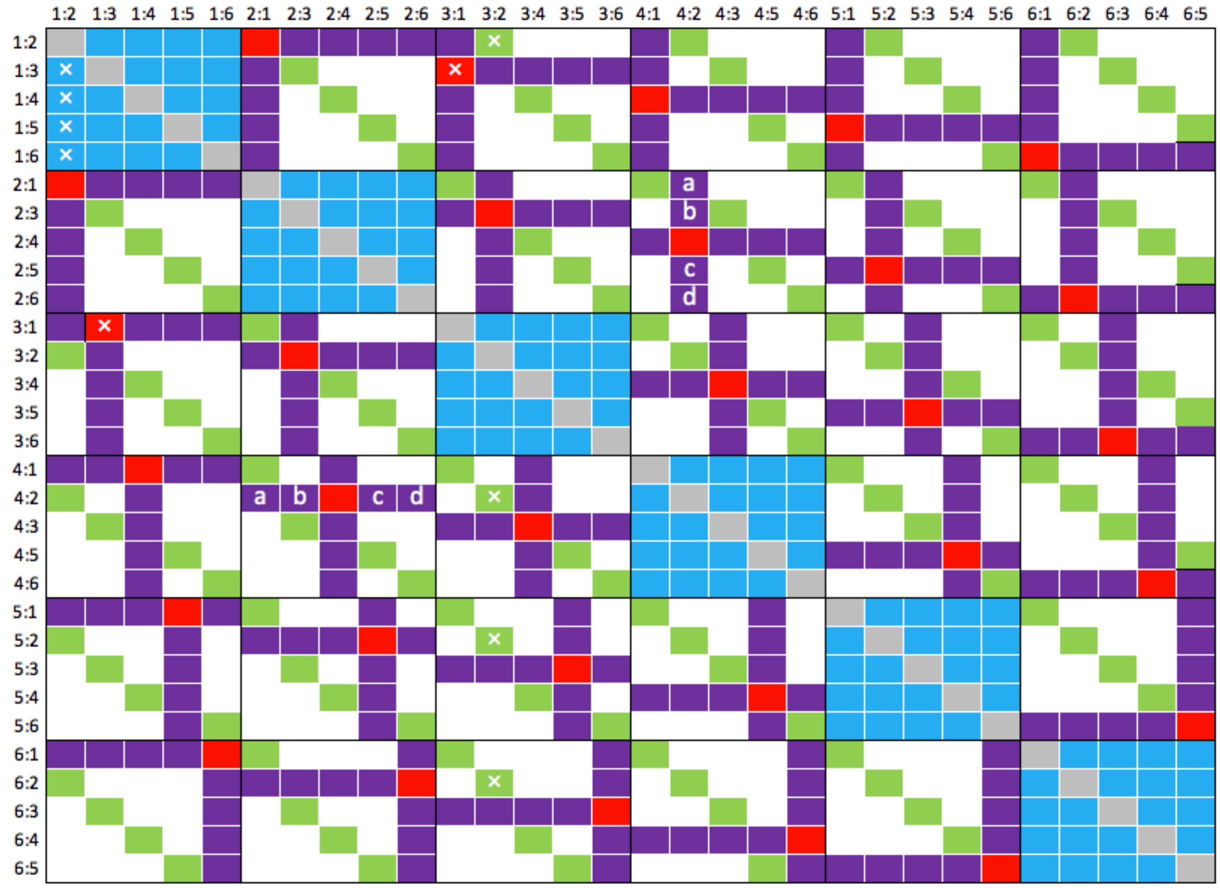
[10]Regarding the two significant interbank connections which arise from significantly negative pairwise correlations, in one of them, we do not distinguish any clear pattern, whereas in the other one, we find that $j = k$. We refer to the latter case as countercyclical lending, because during the period 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.

Second, the blue colored entries in $\widehat{\mathbf{W}}^{\mathbf{H}}$ 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 $\widehat{\mathbf{W}}^{\mathbf{H}}$ 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.

Finally, the violet colored entries in $\widehat{\mathbf{W}}^{\mathbf{H}}$ 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 $\widehat{\mathbf{W}}^{\mathbf{H}}$, 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.

Figure 3: A theoretical interbank connection matrix $\widehat{\mathbf{W}}^{\mathbf{H}}$ illustrating the significant interbank connections types.



Notes: The figure depicts a hypothetical interbank connection matrix $\widehat{\mathbf{W}}^{\mathbf{H}}$, with the aim of illustrating the types of significant interbank connections we have identified when estimating $\widehat{\mathbf{W}}$. Red, blue, green and violet colored entries represent the symmetric, common lender, common borrower and intermediation interaction types, respectively.

In what follows, we analyze the identified significant interbank connections that result from estimating $\widehat{\mathbf{W}}$. To begin with, table 2 reports the frequency with which each interaction type occurs, relative to the total number of significantly positive interbank connections. Interestingly, the table shows that two types of interactions dominate, namely, the symmetric type, followed by the common lender one; with both of them accounting for more than 90% of the significantly positive interbank connections

Table 2: Frequency table of the significantly positive interbank connection types.

Interaction type	**Condition on $\widehat{w}_{i:j,k:l}$**	**Nb of cases**	**Freq**
Symmetric	$i = l$ 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 $\widehat{\mathbf{W}}$, occur. 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.

Second, to further characterize the interbank connections, we now classify the 210 bilateral interbank positions in our dataset into the four identified interbank connection types and examine the banks present in the distinct positions being part of each connection type. Interestingly, table 3 shows that treasury banks, according to Jara and Oda (2015)'s bank categories, have the largest number of symmetric interactions and also, that their share is larger, relative to the fraction they represent in the bilateral interbank positions not being part of the symmetric 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.

Table 3: Frequency table of banks' categories (in percent), distinguishing between the bilateral interbank positions which we classify as belonging to the symmetric interactions and the remaining bilateral interbank positions.

Banks' categories	**Sym interact**	**Non-sym interact**
Big	25	27
Medium-sized	27	55
Treasury	43	11
Retail	5	7
Number of int positions	60	150

Notes: The table reports the frequency table of banks' categories, distinguishing between the bilateral interbank positions which we classify as belonging to the symmetric interaction and the remaining bilateral interbank positions. Banks' categories are big and medium-sized commercial banks, treasury and retail banks, according to Jara and Oda (2015)'s classification. Sym interact and Non-sym interact refer to the distinct bilateral interbank positions being part and not being part of the symmetric interaction type, respectively. Number of int positions stands for number of bilateral interbank positions.

To determine whether treasury banks rely more on relations, we follow Cocco and coauthors and compute lender and borrower preference indices (LPI and BPI, respectively).[11] 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 4 compares the mean LPI and BPI of banks in the distinct bilateral interbank positions being part of the symmetric interactions with the same indices computed over the remaining bilateral interbank positions, distinguishing by banks' categories.

Table 4: Mean LPI and BPI of the banks in the bilateral interbank positions being part and not being part of the symmetric interactions, distinguishing by banks' categories.

	Symmetric interactions		**Non-sym interactions**	
Bank categories	**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 LPI and BPI of banks in the bilateral interbank positions being part and not being part of the symmetric interaction, distinguishing by banks' categories. Banks' categories are big and medium-sized commercial banks, treasury and retail banks, according to Jara and Oda (2015)'s classification. Symmetric interactions and Non-sym interactions refer to the distinct bilateral interbank positions being part and not being part of the symmetric interaction type, respectively.

Table 4 confirms that treasury banks in the bilateral interbank positions which we classify as belonging to the symmetric 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 indices for treasury banks in the two groups of bilateral interbank positions is statistically significant.[12] 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.

[11] 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.

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

Third, in relation to the common lender interactions, we find that all lenders in this type are commercial banks participating in all market segments. In fact, four out of the six distinct lenders involved are medium-sized commercial banks, accounting for 19 of the 23 significantly positive interbank connections with a common lender. In turn, the borrower banks concerned are also homogenous in terms of market focus, since 22 out of the 23 significant interbank connections concern commercial banks. The only exception corresponds to a treasury bank. While homogenous in terms of business strategy, the borrowers involved in this interaction type tend to be more heterogeneous in regards to size.

Fourth, table 5 exhibits an interesting finding, which is that the five lender banks in the common lender interaction type make 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.

Table 5: 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. For the comparison, we only consider bilateral interest rates of term deposits, for which we have information.[13] 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.

[13]For the exercise, 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 secondary market term deposit rate.

There are two possible explanations for the common lender interactions. The first one is that these interactions are simply reflecting that the lenders involved are diversifying their portfolios by lending to the borrowers concerned. According to this view, lenders look at potential borrowers' characteristics to decide whether and by how much to lend, whereas borrower banks would have a more passive role, posting their liquidity needs (for instance, in an auction) to any bank willing to lend to them. Therefore, this explanation would not be a peer effect story. Note that the evidence exhibited in table 5 is consistent with this first explanation.

The second possible interpretation is a peer effect explanation. Manski (2000) identifies three channels through which an action chosen by one agent (in our case, a lending/borrowing decision between two banks 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 channel for the common lender connections would be, when determining which bank(s) to ask for funding, borrower bank j (or bank l) finds informative that bank l (bank j) borrows from bank i and then chooses to follow it by borrowing from the same bank i. In turn, the preference channel would be active if borrower bank j (or l)'s preference for asking for funds to bank i is influenced by the fact and/or the amount that borrower bank l (or j) borrows from the same bank i. Note that both the expectation and the preference channels imply that the peer effects would be operating on the borrower side, that is, that the borrower banks in the bilateral interbank positions being part of the common lender interactions, at least to some extent, would be choosing their preferred lender(s) and when doing so, they may become sensitive to their peers' choices for funding (because of learning or preferences).

Last, a constraint interaction between borrower banks j and l both borrowing from bank i, could occur if the amount bank i can lend to j is limited, at least in some way, by the amount bank i lends to l. Suppose, for instance, that as part of bank i's credit risk management policy, bank i decides to lend to bank j up to a certain level, above which it prefers to lend to another bank, like bank l. However, if this substitution effect between banks j and l were at play, we should observe statistically significant negative pairwise correlations. On the contrary, all the common lender connections are due to statistically significant positive pairwise correlations. Therefore, already at this point, we can argue that the constraint interaction channel is unlikely to play any role.

All in all, the evidence we present provides some support to the first explanation for the common lender connections and does not support the constraint channel of the peer effects interpretation. Still, to determine whether the common lender interactions do reflect peer effects (due to the expectation and/or preference channels) or are simply the result of independent banks' profit maximization/diversification strategies, we need to estimate the spatial autoregressive models, which is the objective of the next section: If peer effects matter, we should 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.

Finally, concerning the low frequency of the common borrower and the intermediation types, the way we read this result is as follows: On the one hand, the low prevalence of the former may be indicating that lenders do not consider other banks' lending choices in the Chilean interbank market when deciding whether and how much to lend to a given bank. On the other hand, the small occurrence of the intermediation type may be suggesting that banks tend to trade in the interbank market, without relying on intermediary banks.

Wrapping up, 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 can not determine whether the significant interbank connections we identify reflect peer effects or not. In the next section, we use the interbank connection matrix to weight the observations and quantify the strength, if any, to which banks' lending and borrowing choices in the interbank market are connected to each other.

4.2 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, whereas 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,[14] standardised and lagged one period, the latter to avoid any endogeneity bias, due to simultaneity.

Specifically, table 6 first presents the estimates of the SAR model, assuming a single autoregressive parameter. Table 7, in turn, reports the estimates of the HSAR model, allowing for heterogenous coefficients.

[14]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.

4.2.1 The homogeneous spatial autoregressive model

Table 6: 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	0.36	49.69	0.00
Lender characteristics			
Non-performing loans	0.01	2.73	0.01
Return on assets	0.01	2.12	0.03
Foreign liabilities	-0.02	-2.99	0.00
Bank deposits	0.02	2.52	0.01
Total loans	0.02	3.24	0.00
Capital adequacy ratio	-0.00	-0.32	0.74
Borrower characteristics			
Non-performing loans	-0.01	-1.60	0.11
Return on assets	-0.01	-2.09	0.03
Foreign liabilities	-0.02	-3.29	0.00
Bank deposits	-0.02	-3.10	0.00
Total loans	0.01	1.79	0.07
Capital adequacy ratio	-0.01	-1.33	0.18
Observations	18,270		
R^2	0.17		
Log likelihood	-18,807		
Number of bilateral interbank positions	210		
Dyadic fixed effects	YES		

Notes: The table reports the spatial panel model estimates with spatially lagged dependent variable, spatial and time period fixed effects. The dependent variable is the de-factored bilateral lending/borrowing positions in the interbank market (de-factored by means of a four-factor model). The covariate total loans includes mortgage, commercial and consumer loans. All the control variables are de-factored, standardized and lagged one period. In blue: 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.

The first important conclusion to extract from table 6 is that the significant interbank connections we have identified when estimating $\widehat{\mathbf{W}}$ do reflect peer effects: The coefficient estimate for $\hat{\psi}$, which measures the strength to which banks' lending and borrowing choices in the interbank market are connected to each other, is significant and positive. On top of that, the estimated $\hat{\psi}$ 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. Recall that $\hat{\psi}$ should range between $(-1, 1)$, with higher values reflecting stronger peer effects.

Second, table 6 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 A4 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 6, 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. Although it is not straightforward to interpret, the positive estimated coefficient may be indicating that banks with larger credit risk do not lend less in the interbank market as a way to send a positive signal to the market (Afonso *et al.* 2014). Alternatively, it may be reflecting that banks simply do not want to hoard cash, when credit risk increases.

Furthermore, table 6 shows that banks with better investment opportunities lend more and borrow less in the interbank market. Intuitively, the positive coefficient estimate for the lenders' return on assets may be reflecting that banks with more profitable investment projects may have lower funding costs, which in turn may allow them to lend more in the interbank market. Last, we find that the more a bank borrows from abroad or the larger the stock of deposits the bank has, the less it needs to borrow from the interbank market. Regarding the positive sign for lenders' foreign liabilities, it may be indicating that a bank borrowing from abroad does not have excess liquidity to lend in the domestic interbank market.[15]

With the objective of assessing the robustness of the previous findings, we conduct two robustness checks. On the one hand, we estimate alternative model specifications to the one in table 6. Among

[15] Although a direct comparison of the least-square coefficient estimates in table A4 with the ML parameter estimates in table 6 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 $(\mathbf{I_N} - \hat{\psi} \times \widehat{\mathbf{W}})^{-1}$, with $\mathbf{I_N}$ 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.

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 6 with the information on the interest rate that banks pay in the wholesale secondary market.

On the other hand, because we find that size and market focus are important determinants of banks' propensity to interact in the interbank 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.[16]

In relation to the robustness check consisting of alternative model specifications to the one in table 6, we conclude that the results we highlight from table 6 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 robustness check based on the alternative weight matrices, we observe that the signs of the model estimates in this case tend to coincide with those reported in table 6. Furthermore, the spatial autoregressive parameter estimates now range between 0.10 and 0.20. Therefore, although the SAR model is not our preferred model, we can still rely on it as a first indication of the importance of peer effects on banks' lending/borrowing choices in the Chilean interbank market.

4.2.2 The heterogeneous spatial autoregressive model

Allowing for parameter heterogeneity, table 7 presents the model estimates of the HSAR. More precisely, it reports the overall mean, median and standard deviation of the $\psi_{i:j}$, $\beta_{\mathbf{il}}$, $\beta_{\mathbf{ib}}$ estimates, the proportion of bilateral interbank positions with statistically significant coefficient estimates (at

[16] 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 $\mathbf{W^{Types}}$, we create a lender-based weight matrix as $\mathbf{W^{Types}} = \mathbf{W^{types}} \otimes \mathbf{I}_n$, with $\mathbf{W^{types}}$ the $n \times n$ weight matrix formed with the banks' categories in Jara and Oda (2015). More specifically, element $w_{i:j}^{types} = 1$ if banks i and j belong to the same category; otherwise, $w_{i:j}^{types} = 0$. 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.

10% significance level), as well as the mean, median and standard deviation, computed only over the significant coefficient estimates.

Table 7: Determinants of the bilateral interbank positions, HSAR model. QML estimates, applied to the de-factored lending/borrowing interbank positions.

	Over all coefficients				Over significant coefficients		
	Mean	**Median**	**Std Dev**	**%Sig (10%)**	**Mean**	**Median**	**Std Dev**
$\psi_{i:j}$	0.17	0	0.40	32%	0.71	0.70	0.17
Lender characteristics							
Non-performing loans	0.01	0.00	0.18	20%	0.06	0.14	0.32
Return on assets	0.02	0.01	0.18	15%	0.02	0.14	0.32
Foreign liabilities	-0.01	-0.01	0.15	15%	-0.02	-0.10	0.28
Bank deposits	0.06	0.04	0.24	18%	0.21	0.30	0.37
Total loans	-0.01	0.00	0.41	17%	-0.06	-0.10	0.74
Capital adequacy ratio	0.01	0.00	0.15	14%	0.02	0.13	0.29
Borrower characteristics							
Non-performing loans	0.00	0.00	0.19	15%	-0.02	-0.11	0.30
Return on assets	0.00	-0.01	0.18	18%	0.02	0.10	0.30
Foreign liabilities	0.00	-0.01	0.18	16%	0.02	-0.08	0.34
Bank deposits	-0.02	-0.02	0.19	10%	-0.05	-0.09	0.31
Total loans	0.05	0.00	0.35	13%	0.17	0.40	0.67
Capital adequacy ratio	-0.01	-0.01	0.14	14%	-0.03	-0.12	0.26

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). The covariate total loans includes mortgage, commercial and consumer loans. All the control variables are de-factored, standardized and lagged one period. %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.

To begin with, table 7 confirms that banks' lending/borrowing choices in the interbank market are related to each other. One way to see it is that the overall mean of the heterogeneous spatial autoregressive parameter estimates continues to be positive and non-negligible, equaling 0.17. On top of that, when comparing the overall mean with the same statistic computed only over the statistically significant parameter estimates, we find that the average impact of the peer effects considerably increases to 0.71, close to the maximum value of 1. In addition, the fact that the mean and median of the statistically significant $\hat{\psi}_{i:j}$ estimates are close together suggests that their empirical distribution is symmetric.

Second, table 7 reveals that the fraction of the statistically significant estimates $\hat{\psi}_{i:j}$, $\beta_{\mathbf{il}}$ and $\beta_{\mathbf{ib}}$ over their corresponding total estimates varies between 32% and 10%. Therefore, it is pertinent to distinguish between the overall statistics and the ones computed only over the statistically significant estimates. Furthermore, the previous two findings reinforce the attractiveness of having a methodology that allows for various degrees of intensity of the peer effects.

Third, in order to investigate the mechanisms through which peer effects 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 4.1. More precisely, table 8 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 $\hat{\psi}_{i:j}$.[17]

Table 8: Analysis of the $\psi_{i:j}$ estimates, when we break down by significantly positive interbank connection types.

Interaction type	**Number**	**Freq**
Symmetric	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. 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.

Table 8 shows that the symmetric and the common lender interaction types continue to dominate. This is because the distinct bilateral interbank positions with significant $\hat{\psi}_{i:j}$, which are part of the symmetric 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.

We can extract two conclusions from table 8. On the one hand, the 58% share that the bilateral interbank positions with statistically significant $\hat{\psi}_{i:j}$ being part of the symmetric interaction type have on the total number of significant $\hat{\psi}_{i:j}$, provides support to the lending/borrowing relation motive for the endogenous peer effects. Furthermore, since treasury banks have the largest number of these symmetric interactions and that, within the bilateral interbank positions which we classify as being part of the symmetric interaction type, they have the smallest number of counterparties (section 4.1), we can further characterize which banks are influenced by this mechanisms.

[17]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.

On the other hand, the evidence in table 8 provides some answers to the open question from section 4.1, namely, whether the common lender interactions were reflecting endogenous peer effects or banks' profit-maximizing/diversification strategies. Precisely, both the 29% and the 39% share that the bilateral interbank positions with significant $\hat{\psi}_{i:j}$ which we classify as being part of the common lender interaction have on the total number of significant $\hat{\psi}_{i:j}$ and on the total number of positions being part of the common lender interaction type, respectively, support, at least partially, the peer effects explanation; in particular, the 39% share would be indicating the relative importance of the peer effect explanation, relative to the profit-maximizing/diversification strategy explanation. Unfortunately, we can not formally test between the two explanations of the common lender interaction.

Regarding the alternative channels for the endogenous peer effects (the expectation and the learning channels), Some anecdotal evidence indicates that interbank loans in Chile are traded both in auctions and over-the-counter (which would be consistent with the expectation and/or the preference channels being at place on the borrower side), with the importance of the latter segment being non-negligible. However, we do not observe the amount of interbank loans traded in each segment. Therefore, we can not extract conclusive conclusions confirming or rejecting any of them.

Fourth, a natural following question would be which bank characteristics make banks more likely to be sensitive to the lending/borrowing 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 $\hat{\psi}_{i:j}$. Table 9 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 9: Analysis of the $\psi_{i:j}$ estimates, when we break down by banks' size, ownership and market focus.

		Over all coefficients				Over significant coefficients			
Characteristic	**Value**	**Mean**	**Median**	**Std Dev**	**Obs**	**Mean**	**Median**	**Std Dev**	**Obs**
Quartile of lenders' assets	1	0.20	0.10	0.46	56	0.74	0.71	0.11	13
	2	0.15	0	0.42	56	0.67	0.67	0.18	7
	3	0.13	0	0.34	56	0.72	0.72	0.34	2
	4	0.22	0	0.37	42	0.71	0.73	0.25	6
Quartile of borrowers' assets	1	0.39	0.36	0.39	56	0.81	0.79	0.14	13
	2	0.09	0	0.33	56	0.60	0.60		1
	3	0.12	0	0.39	56	0.63	0.62	0.19	7
	4	0.06	0	0.42	42	0.62	0.63	0.14	7
If lender is domestic	0	0.19	0	0.43	84	0.73	0.71	0.15	15
	1	0.16	0	0.38	126	0.69	0.67	0.20	13
If borrower is domestic	0	0.23	0	0.45	84	0.80	0.80	0.15	14
	1	0.13	0	0.37	126	0.63	0.63	0.15	14
Lenders' bank cat	Big	0.22	0	0.41	56	0.71	0.73	0.24	8
	Medium	0.15	0	0.40	98	0.71	0.72	0.18	10
	Treasury	0.19	0.10	0.45	42	0.72	0.70	0.09	10
	Retail	0.05	0	0.17	14	-	-	-	-
Borrowers' bank cat	Big	0.09	0	0.43	56	0.64	0.65	0.16	10
	Medium	0.11	0	0.36	98	0.64	0.62	0.14	8
	Treasury	0.44	0.44	0.39	42	0.84	0.86	0.13	10
	Retail	0.15	0	0.32	14	-	-	-	-

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 bank characteristic 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.

Table 9 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 $\hat{\psi}_{i:j}$ 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.

[18] More specifically, for each lender and borrower bank characteristic, we conduct a mean-comparison test, to determine whether the mean of the 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.

Knowing that treasury banks' assets belong to the first quartile of the empirical distribution of banks' assets and that they are foreign banks, one way to interpret the previous finding is that these 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, 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 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.

Fifth, when examining the estimated coefficients for the lender and borrower-specific characteristics, we conclude that the various balance sheet determinants we consider here explain in different manners the evolution of the (de-factored) bilateral interbank positions. As a matter of fact, the mean estimates are more dispersed when we focus on the statistically significant estimated coefficients.

Specifically, focusing on the significant balance sheet estimates, we observe that, with three exceptions, the signs of the mean coefficient estimates in table 7 coincide with those reported in table 6: We continue to find that banks with a larger proportion of non-performing loans lend more and borrow less in the interbank market, whereas banks with better investment opportunities lend more and, contrary to the SAR model estimates, also borrow more in the interbank market. The latter may be because banks with more profitable investment projects may have lower funding costs, which in turn may allow them to lend and borrow more from other banks in the interbank market. In addition, we still observe that the more banks borrow from abroad, the less they lend in the domestic interbank market, while the larger the stock of deposits a bank has, the less it needs to borrow from the interbank market.

In order to investigate the robustness of the previous results, we conduct several robustness checks. First, we consider some of the alternative model specifications that we estimate in the case of the SAR model, 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. Not surprisingly, we find that the findings we highlight from table 7 continue to be valid.

Second, we estimate the HSAR model, relying on the two alternative weight matrices, namely, the matrix based on banks' size and the one based on banks' market focus. Importantly, we conclude that our results are also robust to these alternative weight matrices: The overall mean and median of the heterogenous spatial autoregressive 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.

Wrapping up, the results we exhibit in tables 7, 8 and 9 reveal that there is heterogeneity in the extent to which peer effects matter in the Chilean interbank market. The fact that we propose a methodology 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 and Silva, 2019).

5 Conclusions

The objective of this paper is to propose a flexible methodology to identify and quantify the importance of endogenous peer effects in banks' lending/borrowing decisions in the interbank market. Crucially, our methodology explicitly allows for the possibility of different levels of interaction between banks participating in this market. Our case of application is the Chilean interbank market. Being able to allow for heterogeneity is also possible thanks to the rich and detailed dataset, to which we have access.

One venue of future research 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.

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A Appendix

A.1 Tables

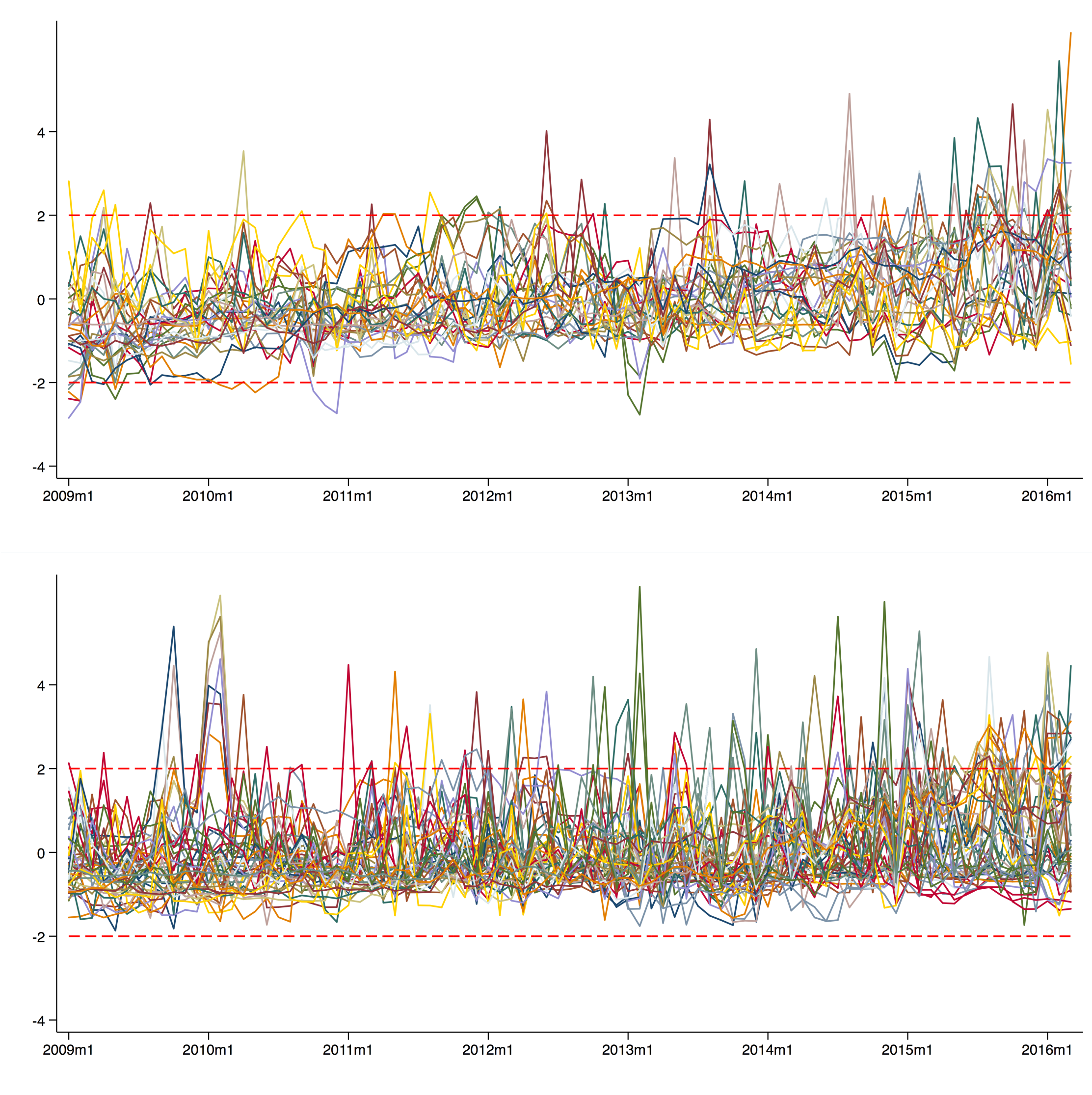
Table A1: Descriptive statistics of the interbank connection matrix

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

Notes: Density is the percentage of significant connections, over the total number of possible connections. Sig stands for significant.

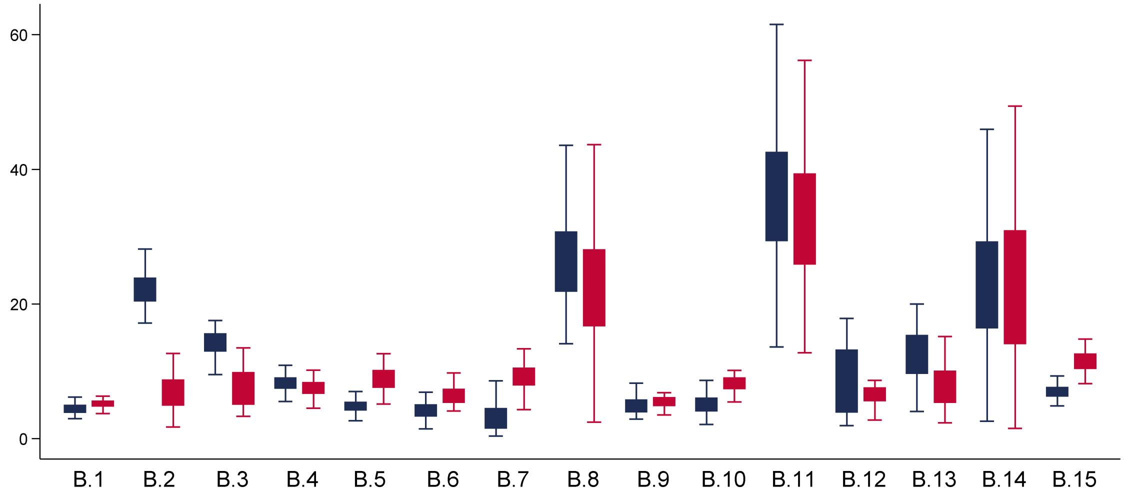
A.2 Figures

Figure A1: Monthly evolution of some of the bilateral interbank positions in the dataset (top and bottom).



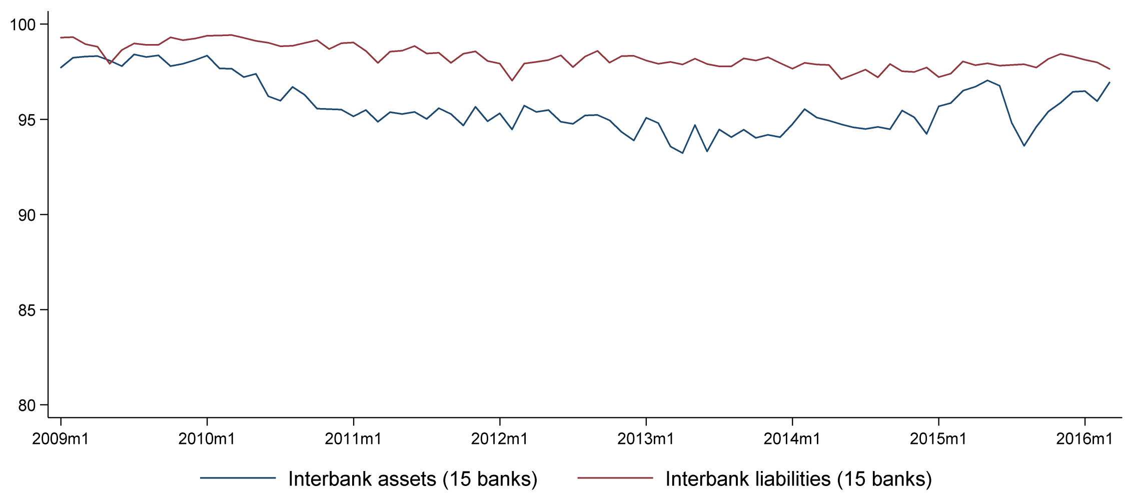
Notes: The figure depicts the monthly evolution of some of the 210 bilateral interbank positions (standardized to have a mean of zero and a standard deviation of one), over the period 2009m1-2016m3. Standardized values. **Data source:** Superintendency of Banks and Financial Institutions and Central Bank of Chile.

Figure A2: Interbank assets (blue) and interbank liabilities (red), over each bank's assets.



Notes: Box plots of interbank assets, over each bank's assets (blue) and interbank liabilities, over each bank's assets (red). Period 2009m1-2016m3. Boxes show percentiles 25^{th}, 50^{th}, 75^{th} and 95^{th} of the monthly distribution. B.1 to B.15 stand for banks 1 to bank 15. **Data source:** Superintendency of Banks and Financial Institutions.

Figure A3: 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, over the period 2009m1-2016m3. **Data source:** Superintendency of Banks and Financial Institutions and Central Bank of Chile.

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 cross-sectional dependence below 0.5 indicates weak cross-sectional dependence in the variable of interest.[19]

Table A2 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^-.

Table A2: 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: CD stands for the cross-sectional dependence test. 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.

[19]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 $\alpha = 1$.

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 $\mathbf{z_{i,t}}$ (the bilateral interbank positions or the bank-specific characteristics):

$$\mathbf{z_{i,t}} = \gamma' \mathbf{f_t} + \xi_{\mathbf{i,t}}. \tag{5}$$

$\mathbf{f_t}$ 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 $\xi_{\mathbf{i,t}}$ 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 A3 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^-.

Table A3: Evaluating the success of the de-factoring, with the exponents of the cross-sectional dependence, for several alternative values of m.

	Degree of cross-sectional dependence (α)								
		m = 1		**m = 2**		**m = 3**		**m = 4**	
Variables	α^-	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: α^- is the exponent of cross-sectional dependence of the raw data, that is, before the de-factoring. α^+ represents the exponent of cross-sectional dependence after the de-factoring. 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.

From table A3, 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 $\mathbf{W}$ with those elements of $\hat{\rho}_{i:j}$ 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 $\hat{R} \equiv (\hat{\rho}_{i:j})$ and show that the non-zeros of $\mathbf{W} = (w_{i:j})$ can consistently be estimated by,

$$\hat{w}_{i:j,k:l} = I\left(|\hat{\rho}_{i:j,k:l}| > \frac{c_p(N)}{\sqrt{T}}\right), \tag{6}$$

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 $\left|\hat{\rho}^1\right|$, the second largest by $\left|\hat{\rho}^2\right|$ 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 $|\hat{\rho}^s| > T^{-1/2}\Phi^{-1}\left(1 - \frac{p/2}{N-s+1}\right)$; 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.[20]

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.[21] 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

[20] 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.

[21] 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.

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 Model specification with independent observations

Table A4 reports the model estimates of specification 3, assuming $\psi = 0$.

Table A4: Panel fixed effects, applied to the de-factored lending/borrowing interbank positions.

Variable	**Coefficient**	**T-stat**	**P-value**
Lender characteristics			
Non-performing loans	0.01	2.38	0.02
Return on assets	0.01	2.08	0.04
Foreign liabilities	-0.02	-3.11	0.01
Bank deposits	0.01	1.59	0.11
Total loans	0.02	3.21	0.01
Capital adequacy ratio	-0.00	-0.54	0.59
Borrower characteristics			
Non-performing loans	-0.01	-0.87	0.39
Return on assets	-0.01	-1.85	0.07
Foreign liabilities	-0.02	-3.55	0.00
Bank deposits	-0.02	-3.39	0.00
Total loans	0.01	2.23	0.03
Capital adequacy ratio	-0.01	-1.47	0.14
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 dyadicfixed 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). The covariate total loans includes mortgage, commercial and consumer loans. All the control variables are de-factored, standardized and lagged one period. In blue: 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.

For robustness, we add to the model specification in table A4 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 A4, 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.