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## **Identifying Complex Core-Periphery Structures in the Interbank Market \***

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### **Abstract**

This paper proposes a framework to identify the structure of a financial network and its evolution of over time, and presents an application to an interbank market with complete actual data. The framework is based on a methodology popular in the social network literature, namely the Stochastic Blockmodelling (SBM), which, we argue, is more general, transparent and richer in results than other proposed methodologies. In particular, we can identify the presence of multiple cores and peripheries, as well as different ways of interaction between them. We find that such a varied core-periphery structure exists in almost all periods for different instruments analyzed. Also, in the case of term deposits, which account for two-thirds of interbank exposures, we find that far from being static, the structure underwent a transition in the period 2009-2015, with the core increasing its size. We also show that facts revealed by our approach cannot be observed in metrics commonly used to describe networks. Finally, we describe how the elements identified by our method can be used to single out sources and channels of transmission of systemic risk in a network of banks.

### **Resumen**

Este trabajo propone un marco para identificar la estructura de una red financiera y su evolución en el tiempo, y presenta una aplicación a un mercado interbancario con datos efectivos y completos. El marco está basado en una metodología popular en la literatura de redes sociales, Stochastic Blockmodelling (SBM), la que, sostenemos, es más general, transparente y rica en resultados que otras metodologías propuestas en la literatura de redes financieras. En particular, nos permite identificar la presencia de múltiples centros y periferias, así como diferentes formas en que estos se relacionan. Encontramos que en casi todos los periodos existe una variada estructura centro-periferia para los distintos instrumentos analizados. Además, para depósitos a plazo, que representan dos tercios de las exposiciones interbancarias, encontramos que, lejos de permanecer estática, la estructura mutó en el período 2009-2015, con un centro que aumentó su tamaño entre otros cambios observados. También mostramos que los hechos derivados de nuestro análisis no pueden ser observados en métricas comúnmente usadas para describir redes financieras. Finalmente, describimos cómo los elementos identificados pueden ser usados para identificar fuentes y canales de transmisión de riesgo sistémico en una red de bancos.

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## 1. Introduction

The systemic implications of a situation of stress in a given financial institution are determined by the structure (Acemoglu *et al*, 2015) and complexity (Caballero and Simsek, 2013) of interconnections in the financial system. Therefore, in order to understand how stress in one part of the network may spread to and affect other parts, it is key to have detailed data on the precise linkages among financial institutions, as argued by Yellen (2013).

However, once data is available – which poses challenges of its own –, we need frameworks to analyze them. This paper proposes one such framework. In particular, one that allows analyzing the evolution of the structure of interbank connections over time in a coherent and informative way.

Most of the related literature<sup>1</sup> focuses on identifying the existence of a structure consisting of a core and a periphery in real-world networks. The framework we propose in this paper allows for a richer characterization of the network’s structure, where a single core-periphery pair is only one of several possible structures that can emerge.

A single core-periphery structure can be defined as the presence of

- (1) a densely interconnected group of intermediaries (the ‘core’),
- (2) a group with weak ties among its components (the ‘periphery’) and
- (3) a strong relationship between the two groups.

Core-periphery structures have been found in different interbank markets. Some authors claim that identifying them is important for understanding and containing systemic risk. For example, Elliot *et al* (2014) study cascades of failures in a core-periphery network. They find that the impact of a peripheral bank on the whole system has an inverted U shape vis-à-vis the level of integration of the core,<sup>2</sup> while the damage caused by the failure of a core bank increases monotonically with the level of integration of the core. Van Lelyveld and in’t Veld (2014), claim that discriminating between banks at the core and at the periphery is “very useful for bank supervision in practice”. Identifying structures that are more complex than a single core-periphery structure substantially enriches the potential analysis.

In this paper we adapt the Stochastic Blockmodelling (SBM) approach (introduced by Holland *et al*, 1983) to characterize the structure of a financial network in an economically meaningful way. With

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<sup>1</sup> Craig and von Peter, 2014; Martinez-Jaramillo *et al*, 2014; Silva *et al*, 2016; Langfield *et al*, 2014; van Lelyveld and in’t Veld, 2014.

<sup>2</sup> The non-monotonic effect of connectedness on systemic impact is reported in Cifuentes *et al* (2005).

this, we can assess whether a single core-periphery structure exists, but we can go further than that, as we show below. We apply the analysis to the database we have built (Carreño and Cifuentes, 2016) with complete daily exposures at the interbank market in Chile for the period from January 2009 to June 2015 over different instruments.

The main contributions of this paper are the following. First, the SBM approach allows a rich characterization of the system, beyond what other methodologies applied in the literature have provided. In particular, we can characterize different ways in which a group of banks belong to the periphery, i.e. whether they are mostly lenders, mostly borrowers, or hold both positions evenly. We can also determine the existence of more than one core. Crucially, our approach identifies these structures from the data, rather than assessing the proximity of the data to arbitrarily pre-defined partitions, as other methodologies do. Second, we can describe the evolution of this rich characterization over time. Third, we provide the network characterization for different instruments of the interbank market. Finally, our results can be used for systemic risk analysis. This can be done in two ways. The first is to use them to map sources of and exposures to risks in the system. Such a map can provide a guide for monitoring and, eventually, regulation.<sup>3</sup> The second is to calibrate the measure of the strength of connections in the core to assess the stance of systemic risk, as described in Cifuentes *et al* (2005) and Elliot *et al* (2014).

We find a varied core-periphery structure in interbank exposures in both term deposits and derivatives, which are the main channels of interbank exposures, representing on average 64% and 15% of total interbank exposures, respectively. In particular, we identify different types of periphery, and periods where more than one center emerges. While the structure seems to be rather stable for derivatives, in the case of term deposits it undergoes substantial changes. We contrast the information elicited by this method with that of a series of commonly used network metrics – which include density, reciprocity, persistence, in-degree and out-degree – and show that the latter cannot provide as rich an account of the network structure, less so of its evolution over time.

This paper is organized as follows. Section 2 introduces the literature review. Section 3 describes our dataset, shows stylized facts of the interbank system and presents a set of commonly used network metrics for the Chilean system. Section 4 presents the methodology of SBM. Section 5 presents the main results, namely, the characterization of the network structure of the interbank market according to SBM. Section 6 concludes.

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<sup>3</sup> Subsection 5.2 discusses implications for monitoring systemic risk of the results of this paper.

## 2. Literature review

This paper is related to multiple strands of the literature on financial networks. First, it relates to papers that propose methods to characterize, in an economically meaningful way, the network structure of the interbank market. In particular, it is closely related to works that test for the existence of a single core-periphery structure in financial networks. Craig and von Peter (2014), devise a procedure for assessing the similarity of real-world networks to a stylized core-periphery structure, which is used, among others, by van Lelyveld and in't Veld (2014), Martinez-Jaramillo *et al* (2014) and Usi *et al* (2017). Langfield *et al* (2014) implement metrics proposed by Borgatti and Everett (1999) similar in spirit to the one just described, in that they search for partitions that minimize a distance to a stylized core-periphery structure. All but one of these works find a core-periphery structure in the interbank markets they study. The exception is Usi *et al, op cit.* who do not find such a structure for the repo market in Mexico.

This procedure has two main disadvantages in relation to the SBM. Firstly, this approach can only say whether data is close to a given structure, while it may be closer to other possible structures. This is important because the types of interrelations among groups of banks that are of interest from a financial stability perspective are multiple. For each pair of groups of banks we can define at least four patterns: lending only, borrowing only, both relations and no interrelation. All of them have an interpretation from the perspective of financial stability. With more groups, possible combinations expand. A strategy that aims to identify the structure that best fits the data by minimizing the distance to stylized structures would have to consider such a large number of possibilities that the exercise could be rendered unfeasible. Craig and von Peter (2014) address this issue by focusing on a specific partition of two groups, which interrelate in a given way. We discuss the merits of this partition in brief. The method we develop in this paper (SBM), in contrast, imposes neither a particular structure of interconnections, nor a number of groups. Rather, the procedure determines the number of groups and uncovers the types of interconnections among and within them, expressed in probabilities.

Second, the procedure does not have a test for the statistical significance of the error score, only a heuristic argument. The SBM, in contrast, provides the statistical significance of the probability of the different types of interconnections among groups.

We now turn to discuss the specific partition proposed in the paper under comment. The stylized structure defined by Craig and von Peter (2014) consists of the following:

- (1) a core where banks have all possible interconnections among themselves,
- (2) a periphery where banks have no interconnection among themselves, and
- (3) banks at the core that lend to and borrow from at least one bank in the periphery.

Deviations from this structure are penalized. The authors argue that this definition ensures that they find a core that “holds the interbank market together.” In this way, they claim, they have identified a group of banks (the core) that plays a particularly important role in the interbank market. We are not sure whether this definition rightly identifies the group of banks that “hold the interbank market together.” On the one hand, intermediation with the periphery need not be done by all banks in the core in both directions, as the structure of penalties requires. Some banks at the core could do the borrowing and others the lending, with funds being intermediated among them within the core. Therefore, the group of banks that “hold the interbank market together” may be larger than the one identified with the definition under discussion here, since banks that do not *simultaneously* borrow from and lend to banks in the periphery, but perform one of these operations, may also belong to that group. On the other hand, a bank can have an important role in “holding the interbank market together” by intermediating between banks at the core only – and therefore “holding the core together” – and not with banks in the periphery. But the minimization of penalties would lead this bank to be classified as part of the periphery since this minimizes the penalty for not transacting with the periphery if it were considered as part of the core. Then, unfortunately, its role in the interbank market would not be identified.

Another approach is proposed by Silva *et al* (2016), who use a heuristic argument to determine the existence of a core-periphery structure from the presence of a rich-club phenomenon in the network and a certain condition on its assortativity. However, they provide no evidence of the robustness of their argument.

In relation to the data, this paper is one of the few works (along with Martinez-Jaramillo *et al*, 2014; Silva *et al*, 2016; Bargigli *et al*, 2013; Langfield *et al*, 2014), that characterize the interbank market (or some network property) using a breakdown of real exposures by instrument. Langfield *et al* (2014) characterize the UK interbank market using cross section data across instruments where each bank reports its exposure to its top-20 bank counterparties. They define two networks: one of interbank exposures and another of interbank funding. They show that the two structures differ. They also find that the networks clearly exhibit a core-periphery structure, but their *strength* (how close the actual structures are to a stylized core-periphery structure) varies by asset class. In contrast, in this paper we have bilateral exposures for all banks on a daily basis for six years, which allows us to complement the static analysis of Langfield *et al* (2014) with a dynamic study of the

pattern of interconnections. Martinez-Jaramillo *et al* (2014) work with a dataset similar to ours for Mexico. In order to monitor systemic risk, they study the topological properties of both the payment system and the interbank market. They find that these networks differ and claim that some network metrics can determine the systemic importance of a bank.

Notwithstanding the importance of having effective bilateral data on interbank exposures, its availability is typically scarce. Anand *et al* (2017) compare different methods for approximating this information from aggregate data.

Finally, this paper is related to works that study systemic risk by asset types (Montagna and Kok, 2013; Poledna *et al*, 2015). These studies conclude that studying systemic risk at the aggregate level may lead to an underestimation of it because of the interaction among instruments that occurs when a bank is involved in several markets with different interconnection structures. In this work, we show that the most important instruments in the interbank market, i.e., term deposits and derivatives, have different patterns of interconnections.

### **3. Data, stylized facts and network metrics**

In this section we describe our dataset. We include in this description some network metrics commonly used in the literature, namely density, reciprocity, persistence, in-degree and out-degree. We present these metrics in order to compare the picture they provide of the interbank network with that conveyed by the method we propose here.

This paper uses a dataset built from regulatory data of interbank exposures of Chilean banks (Carreño and Cifuentes, 2016). Chilean banks report their interbank assets and liabilities on a daily basis in eight categories.<sup>4</sup> Available data goes from January 2009 to June 2015. We consider all twenty-three banks in operation in January 2015.<sup>5</sup>

#### **3.1 Size and participation of banks in the interbank market**

We begin by showing some stylized facts over the size of the interbank market and the participation of banks in it. Similarly to other countries, interbank exposures represent an important share of the

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<sup>4</sup> See Table A.1 for more details. Also, see Carreño and Cifuentes (2016) for further description of the data.

<sup>5</sup> During the period under study, some small banks were created and others ceased to operate. Their participation in the interbank market was minimal or non-existent, so they are not included in the analysis in order to economize on explanations of dynamics of lesser importance. In addition, in November 2009, a small bank merged into a medium-sized one. For the same reason, we treat this bank as if the merge had occurred at the beginning of the period. To implement this, we consolidate the interbank positions of the pair, eliminating the positions among them. Finally, three other small banks are excluded from the analysis for having a sporadic and minimal participation.



balance sheets of banks.<sup>6</sup> Figure 1 shows the stock of interbank assets (positive values) and interbank liabilities (negative values) by bank at the end of the month for the 23 banks, as the percentage of total assets of the system. Interbank exposures represent on average 7.3% of the system's assets, positioning them as the second source of wholesale funding via term deposits of Chilean banks, behind Mutual Funds (9.7%) but ahead of Pension Funds (4.9%), in the same period.

[Insert Figure 1]

There is high heterogeneity in the participation of banks in the interbank market. Small-sized banks have more interbank assets and liabilities than large banks in relation to their balance sheets. Figure 2 shows the distribution of the interbank assets and liabilities for each bank in relation to their total assets. In order to preserve anonymity, we group banks into two categories: large and medium-sized banks (eleven banks) and small banks, which are mostly oriented to consumer lending and treasury activities (twelve banks). While interbank exposures represent, on average for the sample, 6% of assets for large and medium-sized banks, for small banks interbank exposures can reach 40% of their assets.<sup>7</sup> We also find that the relation between asset and liability positions of banks is heterogeneous. While some banks regularly have asymmetric positions in the interbank market (net lenders or net borrowers), other banks maintain a balanced position.

[Insert Figure 2]

By type of instrument, the most relevant are Term deposits and Derivatives, which represent 64% and 15.3% of interbank exposures, respectively. For this reason, we focus on these two for our analysis.<sup>8</sup> See Table A.1 for more details.<sup>9</sup> For simplicity of exposition of our results (section 5) we work with end-of-month data only. Our dataset contains information of effective interbank exposures for twenty-three banks on end-of-month data from January 2009 to June 2015. The full dataset therefore comprises 78,936 elements ( $23 \text{ banks} \times 22 \text{ counterparties} \times 2 \text{ instruments} \times 78 \text{ months}$ ).

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<sup>6</sup> According to Bankscope data for 225 banks around the world, interbank exposures represented approximately 6.8% of the system's assets in 2015.

<sup>7</sup> This implies that risks associated with the interbank market can be significant, since large and medium sized banks expose approximately 50% of their capital on the interbank market (capital represents 10% of their assets on average), while small banks expose between 200% and 300% of theirs (capital represents 15% of their assets on average).

<sup>8</sup> In other countries the situation is different. For example, in the UK, marketable securities (term deposits) account for 16% of total interbank exposures, while derivatives and unsecured loans (interbank loans) represent 44% and 25%, respectively. On the funding side, repo and unsecured loans represent 66% and 29% of the total interbank funding, respectively (Langfield *et al*, 2014). In Mexico, in turn, repos represent more than 50% of the interbank market (Molina-Borboa *et al* 2015). Thus, the use of term deposits for funding, instead of repos, seems to be particular of the Chilean interbank market, which is relevant considering that repos have collateral and term deposits don't.

<sup>9</sup> We do not consider outstanding payments because the associated credit risk is covered by the backstops of the corresponding settlement system.

### 3.2 Network metrics for the interbank market

We now characterize the network formed by banks on term deposits and derivatives using metrics commonly used in the literature on financial networks. The objective is to let these metrics inform us about the network we are dealing with, and then see to what extent the results of our SBM methodology enriches our understanding of the network. In particular, in this section we report the density, reciprocity and persistence of interconnections.<sup>10</sup>

#### 3.2.1 Density and Reciprocity

For a given number of banks ( $N$ ), density is the percentage of effective links over total possible links ( $N \times (N-1)$ ). Reciprocity, in turn, follows the same definition but considers only reciprocal links (bank  $i$  lends to bank  $j$ , and bank  $j$  lends to bank  $i$ ). Figure 3 shows in a daily frequency the density, reciprocity and the non-reciprocal links for term deposits (a) and derivatives (b). Density for term deposits is 30% on average. Comparing this number internationally is difficult for two reasons: actual data is typically scarce, and systems with different number of banks are not comparable, unless one has access to extensive micro-data in order to measure density of subgroups of comparable size.<sup>11</sup>

The density increased from 25% to 40% between mid-2009, by the end of 2011. This phenomenon is probably related to the Term Liquidity Facility introduced in June 2009,<sup>12</sup> which encouraged the purchase of bank deposits because they could be used as collateral to obtain liquidity from the Central Bank.

[Insert Figure 3]

After 2013, despite decreasing somewhat, density remained at a higher level than in 2009 by an important margin. Thus, a significant fraction of the new interconnections created between 2009

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<sup>10</sup> In addition, we present out-degree and in-degree of interconnections in the appendix (Figure A.2).

<sup>11</sup> The density of a network is related to the number of nodes (banks). For example, if banks create a fixed number of interconnections, the density of that network tends to zero as the number of nodes increases. This caveat notwithstanding, we report some statistics for other countries. Craig and von Peter (2014) report, for the case of Germany with 2,000 banks, a density of 0.41%, Soramäki *et al* (2006) report for the United States with 5,086 banks, a density of 0.3%, and Pröpper *et al* (2008) report for the Netherlands, with 183 banks, a density of 12%.

<sup>12</sup> In July 2009, at a time of high global uncertainty due to the global financial crisis, the Central Bank of Chile established a Term Liquidity Facility (FLAP) for banks. This facility lent against collateral at a fixed rate equal to the monetary policy rate, at 90 and 180 days. Eligible collateral for the FLAP included Central Bank instruments, term deposits issued by banks, and bank mortgage bills. The facility was closed in May 2010.

and 2011 persisted over time.<sup>13</sup> Interestingly, the figure also indicates that a large percentage of these new interconnections were reciprocal.

In the case of derivatives, the density is even higher, reaching on average 50% of all possible interconnections. Unlike the case of term deposits, this has remained constant over time, after a small increase at the end of 2010.

Regarding reciprocity, we find that it is high for term deposits—in the sense that most links are reciprocal—, but even higher for derivatives. In the former, we find that on average more than half (57%) of interconnections in this market are symmetrical (reciprocal). In derivatives, in contrast, we find that on average almost 90% percent of interconnections are reciprocal. The result of high reciprocity of observed interconnections may have important implications in terms of reducing systemic risk. In particular, if we consider that in derivatives there is *close-out netting*<sup>14</sup> in the case of counterparty default, the systemic risk in this market is limited, because the bilateral positions cushion the impact of a bank failure.

### 3.2.2 Persistence of the interconnections

As for persistence, Figure 4 shows for each date the percentage of observed links that will still exist after a given horizon. Density is also included to support the analysis. We find that persistence remains high over time, especially for derivatives, which confirms for Chile the evidence found for other jurisdictions that interbank relations are stable.<sup>15</sup> However, we also find cyclical variation on the metric of persistence over time, especially for term deposits. For example, linkages observed by the end of 2009 seem to have been particularly persistent. Indeed, around 95% of them lasted for at least two years. This high persistence decreases over time, stabilizing in the second half of 2012, where observed links that last for at least a year are around a still high 80%.<sup>16</sup> This cyclical variation is probably linked to the reactions to the Global Financial Crisis of 2008, and the facility introduced by the Central Bank mentioned before.

[Insert Figure 4]

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<sup>13</sup> In particular, roughly 50% of the interconnections created in this period were still active in June 2015 (results not shown here).

<sup>14</sup> For a detailed discussion of close-out netting in Chile, see Box V1.1 in Central Bank of Chile (2009).

<sup>15</sup> See Cocco *et al* (2009). Also Molina-Borboa *et al* (2015), who document link persistence in the Mexican interbank market.

<sup>16</sup> It should be noted that the observed high persistence is not explained by the fact that term deposits have a long maturity. Actually, term deposits have a mean term of 90 days, while persistence is high for terms up to two years.

Overall, network metrics tell us about an interbank market of term deposits where density significantly increased up to the beginning of 2011, and then showed periods of stability, mild decrease and rebound. That dynamic closely mirrors that of reciprocal links. We also know that persistence of links for periods of a year or longer, while still high, decreased progressively since 2009 onwards. In the case of derivatives, metrics do not show a similar cyclical variation as those of term deposits – being more stable – but exhibit comparatively higher density, reciprocity and persistence. Differences across instruments are also found by both Bargigli *et al* (2013) for the Italian interbank market, and Molina-Borboa *et al* (2015) for the Mexican interbank market.

We observe that term deposits and derivatives differ in all metrics, with derivatives having more density, reciprocity and persistence. Figure A.2 verifies that they also have higher in and out-degree, which is consistent with higher density and reciprocity. While beyond the scope of our paper, we venture a hypothesis for what could explain these differences. It should be considered first that regulation of banks in Chile limits the currency mismatches that banks can have. Derivatives play an important role in closing currency positions arising elsewhere in the balance sheet of banks. Crucially, the existence of close-out netting mentioned before, could lead banks to a risk management strategy featuring, simultaneously, a wide range of counterparties, and a low net exposure with each of them. Close-out netting may lead banks to be more open in relation with whom they enter into a relation with. But in order to keep exposures at bay, in the presence of close-out netting, reciprocal positions are required. In this way, a higher number of counterparties with reciprocal positions may arise.

#### **4. Methodology: Stochastic Blockmodelling**

In this section we present the Stochastic Blockmodelling methodology, which provides a rich description of the system’s structure and evolution over time, allowing us, among other things, to assess whether a core-periphery structure exists in the interbank market.

The goal of blockmodelling, introduced by Holland *et al* (1983), is to reduce a large, apparently incoherent network to a smaller, comprehensible structure that can be interpreted more readily. Blockmodelling, as an empirical procedure, is based on the idea that nodes (banks) in a network can be grouped according to the extent to which they are equivalent, following a meaningful definition

of equivalence.<sup>17</sup> In this way, the SBM framework defines a probability distribution over the network  $X$ ,  $Pr(X|K, Z, \boldsymbol{\pi})$ , where  $K$  (number of groups),  $Z$  (the group assignment of each bank) and  $\boldsymbol{\pi}$  (the edge density among groups) govern the probabilities of an interconnection under the model. So, the aim of the SBM is to find the values of  $K, Z, \boldsymbol{\pi}$  that maximize the probability of seeing the observed data  $X$  under the distribution  $Pr(X|K, Z, \boldsymbol{\pi})$ .

In what follows, we formalize the Bayesian version of the SBM process and then present the results.

#### 4.1 Frequentist vs Bayesian approach to SBM

There are several methods for finding the most accurate partition of a given network (model selection) in the context of SBM.<sup>18</sup> For example, the frequentist approach focuses on comparing among pairs of alternative candidate models and selecting the one with the highest fit. However, point estimates like the maximum likelihood lead to over-fitting. Models with more parameters fit the data better than simpler models, because the latter are less responsive to noise in the data. Conversely, the Bayesian framework has a natural built-in penalty for more complex models in the *marginal* likelihood, avoiding the problem of the frequentist approach. For this reason we follow the Bayesian approach to find an informative partition of the data.

#### 4.2 Bayesian Approach

We present the Bayesian approach proposed by Nowicki and Snijders (2001), defining first the group assignment of banks. So, given a number of banks ( $N$ ) and a number of groups ( $K$ ), which we take as given for the moment, we assume that the membership of a bank  $i$  in group  $k$  follows a multinomial distribution

$$z_i \sim \text{multinomial}(1; \theta_1, \dots, \theta_K), \quad (1)$$

where  $\theta_k$  is the probability of a bank of being assigned to a group  $k$  ( $1 = \sum_{k=1}^K \theta_k$ ). In turn, the vector  $\boldsymbol{\theta}$  is itself a random variable that, for mathematical convenience, is drawn from a Dirichlet<sup>19</sup>

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<sup>17</sup> Because of the stochastic nature of the methodology, banks are grouped based on their stochastic equivalence, where two banks are stochastically equivalent if they are exchangeable from the point of view of the probability distribution. Therefore, it is not necessary that those two banks have the same interconnections, only that they have the same probability of creating an interconnection with banks in another group.

<sup>18</sup> For more detail about the exact strong and weak conditions for community detection, see Abbe and Sandon (2015).

<sup>19</sup> The choice of the *Dirichlet* distribution is not casual, since this distribution is the conjugate of the multinomial and a bivariate version of the beta distribution, which allows defining a posterior that can be solved analytically.

( $\theta \sim \text{Dirichlet}(\lambda)$ ) with parameter  $\lambda$ , that is assumed equal to 1 (uniform prior) in order to express ignorance about the real parameters.<sup>20</sup>

Having defined how  $N$  banks are assigned to  $K$  groups, we describe how, given  $z_i$ , the interconnections between banks are created. First, we define the matrix of probabilities  $\boldsymbol{\pi}$ , a  $K \times K$  matrix that shows the probability of banks forming links both within their groups and with others, whose elements we assume follow a Beta distribution,

$$\pi_{kl} \sim \text{Beta}(\alpha, \beta), \quad (2)$$

where  $\alpha$  and  $\beta$  are the coefficients of the distribution, which we assume equal to 1 (uniform prior). Then, having defined the probability of creating an interconnection across groups of banks, the existence of an interconnection between two banks follows a Bernoulli distribution,

$$x_{ij}|K, Z, \boldsymbol{\pi} \sim \text{Bernoulli}(\pi_{z_i z_j}), \quad (3)$$

where the probability of creating an interconnection between bank  $i$  and bank  $j$  depends on the group assignment of banks ( $\pi_{z_i z_j}$ ). So, it is assumed that, given  $K$  and  $Z$ , the interconnections are formed independently within a group, so that

$$P(\mathbf{X}|K, Z, \boldsymbol{\pi}) = \prod_{ij} \pi_{z_i z_j}^{x_{ij}} (1 - \pi_{z_i z_j})^{1-x_{ij}}, \quad (4)$$

where  $P(\mathbf{X}|K, Z, \boldsymbol{\pi})$  is the likelihood function. Finally, using Bayes's Theorem, we define the problem in the following way:

$$\underbrace{P(Z, \boldsymbol{\pi}|\mathbf{X})}_{\text{Posterior}} \propto \underbrace{P(\mathbf{X}|K, Z, \boldsymbol{\pi})}_{\text{Likelihood}} \underbrace{P(Z, \boldsymbol{\pi})}_{\text{Prior}} \quad (5)$$

so that the posterior is defined by the likelihood function and the priors. In this way, the Bayesian approach to the SBM is complete, and the estimation of the posterior gives us the parameters of interest.

In addition, although the whole process is done by defining a given  $K$ , we would like to randomize this variable too. Here, and following Aicher *et al* (2015), we describe an approach for choosing  $K$ , based on Bayes factors.

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<sup>20</sup> Note that the uniform prior does not have much influence on the results of the statistical analysis when the data provide more information than the prior, which seems to be the case for the estimation and prediction of stochastic blockstructures (Nowicki and Snijders, 2001).

Let  $\mathcal{M}_1 = (K_1, Z, \boldsymbol{\pi})$  and  $\mathcal{M}_2 = (K_2, Z, \boldsymbol{\pi})$  be two competing models, one with  $K_1$  groups and the other with  $K_2$  groups. The Bayes factor between these models is

$$\log B(\mathcal{M}_1, \mathcal{M}_2) = \log \frac{P(X|\mathcal{M}_1)}{P(X|\mathcal{M}_2)}, \quad (6)$$

where  $\mathcal{M}_1$  is, for example, a model with  $K = 2$  and  $\mathcal{M}_2$  is a model with  $K = 3$ . So, the greater the difference between these two models, the greater the Bayes factor, rejecting  $\mathcal{M}_2$  for  $\mathcal{M}_1$ . In this work and without being limiting, we tested for  $K$  equal to 2, 3 or 4.<sup>21</sup>

Summing up, the procedure can be described as follows: given an observed network  $\mathbf{X}$ , SBM searches  $Z$ ,  $\boldsymbol{\pi}$  and  $K$  such as to maximize the probability of observing network  $\mathbf{X}$ . To implement this procedure, we use the algorithm developed by Aicher *et al* (2015), who derive a variational Bayes algorithm for efficiently learning stochastic block model parameters (weighted and unweighted) from the data.

## 5 Structure of the interbank market: Core-periphery and beyond

We now turn to our main results. The SBM is applied to each date (despite having daily data, we work with the last day of each month of the 78 months available to keep the presentation of results simple),<sup>22</sup> giving us, for each date, a group assignment ( $Z$ ), and a matrix of probabilities ( $\boldsymbol{\pi}$ ) associated with the number of groups ( $K$ ), that in our exercise are 2, 3 and 4. We arrange the groups according to their internal probability of interconnection. Therefore we call the ‘first group’ the one with the highest probability of interconnection among its members, ‘second group’ the one with the second-highest probability, and so on.

With regards to robustness of group formation, in the Bayesian framework we can calculate the posterior probability of a bank being assigned to a given group. The method chooses an assignment of banks to groups such that it maximizes this probability. A larger probability means a more robust assignment. For the case of term deposits, we find that 94% of the total assignments (23 banks  $\times$  78 months = 1,794 assignments) have a probability equal to or higher than 90%. On the contrary, only

<sup>21</sup> As argued by Aicher *et al* (2015), this method has produced good results on synthetic data with known planted parameters.

<sup>22</sup> Note that each period is estimated independently, despite the described persistence in the data. If computational capacity were a limitation, estimation could be made more efficient using the information on persistence by implementing a search of the efficient allocation in the vicinity of the one of the previous period. However, the risk of local maximums will always be lurking. Since in our exercise computational capacity is not a problem, we run the search from scratch in every period.

1% of total assignments have a probability lower than 50%. In these cases the method assigned those banks to the group with the higher probability of belonging, but there were other alternatives with significant probabilities. The same is true for derivatives. We find that 95% of total assignments have a probability equal to or higher than 90%. On the contrary, just 0.6% of the total assignments have a probability lesser than 50%. These results indicate that assignments in both instruments are highly robust.

## 5.1 Patterns of interconnections

We begin by studying the pattern of interconnections. Table 1 and Table 2 report the 50<sup>th</sup> percentile of cells of matrix  $\pi$ ,<sup>23</sup> i.e. the median probability of forming an interconnection between and within different groups, for the cases where the estimation procedure indicates that there are three and four groups, respectively ( $K$  equal to 3 and 4, respectively). The row indicates the group of banks that borrow and the column indicates the group of banks that lend.

[Insert Table 1]

[Insert Table 2]

In what follows, we describe the case of four groups (Table 2) beginning with panel (a), Term deposits. We find that the median probability of observing an interconnection among banks in the first group is 82%, in contrast to the second, third and fourth groups, where the probability is 28%, 7% and 1%, respectively. Banks in the second group have a stronger probability of forming a link with banks in the first group than with banks in their own group. In effect, the probability of seeing an interconnection between a bank in the first group and one in the second is either 88% or 40%, depending on whether the second group lends to or borrows from the first group, respectively. In contrast, the probability of seeing an interconnection among banks of the second group is only 28%. The third and fourth groups show a similar feature.

The described configuration, namely, one group with high probability<sup>24</sup> of its members being linked to each other, and other three groups where the probability of having a link with the first group is higher than that of having links amongst its members, fulfills the definition of a core-periphery structure, with the first group being the core while the others are the periphery. However, we do

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<sup>23</sup> The full distribution of  $\pi$  is presented in Table A.3.

<sup>24</sup> The next sub-section presents the threshold values with which we label probabilities as low, medium and high.



more than simply verify the existence of such a configuration, but we can advance significantly in its description as compared with other approaches.

First, we observe that there are different groups in the periphery. In the case we are analyzing, there are three of them. Second, we can also see that, sometimes, the relation between groups in the periphery and the center is not symmetrical. In fact, in particular for the second and the fourth group, the periphery is more likely to provide funds to the center, rather than being funded by it.

The latter point is highly relevant. It is common that core-periphery structures are analyzed assuming that the core, amongst other characteristics, intermediates funds from and to the periphery. Our method allows us to inspect whether this is so, and we see, quite often, a core that mostly funds itself from the periphery, rather than intermediating among members of the periphery. This implies different consequences in terms of systemic risk. In particular, the credit risk that members of the periphery can impose on the core is negligible.

It should also be highlighted that the method allows the identification of more than one core. This phenomenon does not occur too frequently in the specific case studied here. Therefore, it does not show up in the median levels reported in tables 1 and 2. The way it would show up would be as a second group with a probability of members being linked to each other higher than the probability of having a link with other group. We will be able to observe this case in the next sub-section, where we describe a framework to present all relevant structures in the data.

In derivatives (panel b of Table 2), in turn, we find that the probability of forming an interconnection inside the first group is 88%, which contrasts with the other groups, where the probability of forming an interconnection within the same group is 57%, 9% and 2 %, respectively. Members of the second, third and fourth groups have a likelihood of having links with banks in the first group that is higher than the likelihood of having links among themselves. This makes the first group the center and the others the periphery. With regards to symmetry, unlike term deposits, the interconnections between the first and the second group are symmetric. The probability of the second group having an active position with the first group is 95%, and the probability of having a passive position with the first group is 94%. Comparing with term deposits, the extent of reciprocity seems higher for Derivatives.

## **5.2 The dynamic of the network structure**

The richest part of the results of this work lies in that we can identify different patterns of interconnections for groups of banks, and track their evolution over time. We look at the number and types of groups found for each date. To organize the information visually, we create a timeline for each bank, where in each month we indicate the group to which the bank belongs. On each date, banks can change the group they belong to. Also, the existing groups may change.

[Insert Figure 5]

### 5.2.1 Types of groups

Figure 5 describes the groups found based both on their characteristics and on the observed relation with other groups. Since we consider only relations between pairs of groups, patterns can be adequately represented in 2-by-2 matrices. We adopt the convention of defining types of a *core* group, or of the *main core* group when there is more than one, based on their own characteristics (in particular, the strength of the links within the group of banks); while the types of groups in the *periphery*, and of the *non-main cores* were they to exist, are determined by the attributes of their relation with the (*main*) *core*.<sup>25</sup> If there is more than one *core*, we define the *main core* as that with the strongest within links.

We mark each quadrant of matrices in Figure 5 with the letters H, M and L, indicating a high ( $Pr > 75\%$ ), medium ( $40\% < Pr < 75\%$ ), and low ( $Pr < 40\%$ ) probability of forming an interconnection.<sup>26</sup> In Figure 5 we also introduce a color coding to identify groups. Any group of banks with a high or medium probability of forming links amongst themselves will be called *Core*. We mark them in red (matrix a) if their within probability is high. If the highest within probability is medium, banks will be marked in orange (matrix b). Next, in the cases where a second core appears, we observe two possible patterns of interrelation with the main core: one where banks in the second core have a high probability of lending to banks in the main core, but a low one of borrowing from them (blue, matrix c), and other where both types of relation with banks in the other core have a high probability (grey, matrix d).

Regarding the groups with low probability of forming links among themselves, three of them, groups (e), (f) and (g), fulfill the definition of periphery, that is, having a probability of links with

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<sup>25</sup> The relationship between non-core groups can give rise to further characterization of sub-groups. We do not explore that avenue to maintain the presentation of results tractable, but also because they do not seem relevant in the case we are analyzing: the large majority (75%) of relationships between non-core groups has a median probability of occurrence lower than 4%, as can be verified in tables 1 and 2.

<sup>26</sup> These thresholds are set heuristically based on the observed probability distributions of banks in two groups having an interconnection.

the core which is higher than the probability of links among themselves. Group (e) has a symmetrical relation with the core, (f) is similar to (c) in that its lending relationship with the core is strong but its borrowing relationship is weak, while (g) groups banks with a higher likelihood of being funded by the core rather than funding it. Finally, group (h) accounts for those banks with low probability of forming links with anyone in any sense – i.e. disconnected banks –, so they do not really fulfill our working definition of periphery.

Two points should be emphasized. First, we are interested in the relationship with the core; hence we do not consider the relation among non-core groups (for example, the second with the third group in Table 1 or 2). Second, we note that elements in Figure 5 do not cover all the possible ways in which groups may relate with the center; only the observed ones.

### *5.2.2 A guide to systemic risk assessment*

As a guide to systemic risk assessment, the information provided by this analysis is rich and essential. To begin with, diagrams inform us that core groups are highly likely to be funded by groups (c), (d) and (f): see the high probability in the upper right-hand cell. This information identifies groups subject to be monitored in terms of their capacity to provide funding. At the same time, by definition, the three groups identified are exposed to solvency problems in core groups. This should also be part of the mapping of systemic risks and channels of transmission that serves as an input to determine monitoring priorities. Group (e) can also be monitored under the same lens, although with a lesser intensity. On the other hand, group (d) depends highly on funding from the core (high probability in the lower left-hand cell). This makes this group likely to be impacted by a curtailment in lending capacity of the core, while – similarly to the previous case – the core is exposed to solvency problems in group (d). Groups (e) and (g), in turn, are involved in the same risk relations but with a lesser intensity. Finally, group (h) has low probability of being involved in interbank relations. Therefore, it neither is exposed to risks from, nor imposes risks to, other banks, of the sort identified here.

### *5.2.3 Membership and evolution over time*

Figure 6a maps the pattern of interconnections of all banks over time for term deposits. Banks are listed on axis Y and time runs over axis X, and we assign to every bank and month the color of the group the bank belongs to. Figure 6b provides an alternative view of the same information. Here, rather than tracking the situation of individual banks over time, we follow the evolution of groups,

following the same color codes. We order groups according to whether they represent a core, a periphery or neither (disconnect component). For visual clarity, we introduce a space between the three categories so their evolution can be easily observed. Series are shown in a six-month moving average, in order to smooth out shorter term fluctuations.

[Insert Figure 6]

The first salient fact in Figure 6a is that the large majority of banks change the way they relate to others over time. This validates analyzing the evolution of the structure over time. The second is that a core-periphery structure of the interbank market exists in almost all periods, although its nature varies significantly. This is more evident in Figure 6b. The existence of a core-periphery structure is verified by considering that in almost every period there is at least one group of banks with high (red), or medium (orange and navy blue) probability of being connected amongst themselves, and other groups with a lower probability of being connected amongst themselves but a higher one of being connected to the core. The latter are the periphery. There are only three periods in which the only group that exists in addition to the core is the type (c) (light green, disconnected), which does not fulfill the specific definition of periphery that we are considering in this work. A third salient fact is that a second core shows up in some periods, particularly in the second half of the period, the group represented by banks in navy blue color. It should be noted that the fact that towards the end of the period Figure 6b shows three cores present at the same time (red, orange and navy blue), this is just a consequence of these series being moving averages. Red and orange cores never co-exist, as can be verified in Figure 6a.

A fourth salient fact, and perhaps the most interesting one, is that it is possible to observe, both in Figures 6a and 6b, a rich dynamic in the structure of the system. Three stages can be observed. A first stage runs between January 2009 and July 2010. In this stage there is a core with varying strength (red and orange), and whose membership seems to progress towards consolidation. At the beginning of the period, a small second core shows up (navy blue). During the period, three types of periphery are observed, one that mostly borrows from the core (yellow), another that mostly lends to the core (light blue), and a third that both borrows and lends (dark green).

A second stage runs between August 2010 and October 2013. This period is characterized by the consolidation of two groups, the core (red) and a periphery with strong lending ties to the core (light blue). By November 2012, the second group (light blue) strengthens the relations amongst themselves becoming a second core.

A third stage runs from November 2013 to the end of the sample, June 2015. The period is characterized by a return to instability in the structure of the system, but this time in the direction of banks increasing links amongst themselves. Broadly speaking, members of the main core (red) weaken their links (orange), and sometimes increase their lending to members of the second core, becoming one large core group. Groups in the periphery are rather small and sporadic, with the one that borrows from the core (yellow) having more presence. It is important to highlight that none of the standard metrics in network analysis (density and reciprocity, persistence, in-degree and out-degree in Figures 3a, 4a, A.2a and A.2b, respectively) would give the slightest hint of an evolution of this sort.

For derivatives, it is possible to identify four groups (Figure 7). A main core (red), a second core with symmetrical links to the other core (gray), and a periphery characterized by symmetrical links with the core (dark green). A fourth group (light green) does not fit the definition of periphery used in this paper.

[Insert Figure 7]

Two important differences can be highlighted vis-à-vis the case of term deposits. One is that we do not observe a rich dynamic in the market structure for this instrument. In the first half of 2010, a group of banks consolidates a periphery (green). Other than that, most banks show some variability, but to and from one or two patterns. Secondly, the two types of groups other than the main core show symmetrical links with it. It is interesting to note that these patterns (dark green and grey) have no presence at all in the term deposits market, pointing to the fact that in the latter the periphery has mostly non-symmetrical relations with the core, while the opposite is true for exposures from derivatives. Finally, while the periphery shrank substantially in 2013 and kept that way until the end of the sample, in derivatives there is a trend of a core that shrinks and a periphery that expands gradually.

### **5.3 A possible narrative**

We close this section by briefly offering a possible explanation of the observed changes in the structure of the interbank system in Chile. This goes beyond the objectives of the paper, which were to develop a method for analyzing interbank systems using Stochastic Blockmodelling techniques, so they should be considered as an untested hypothesis.

It is unfortunate that complete data of effective interbank exposures is available starting only in January 2009, i.e. in the aftermath of the Global Financial Crisis (GFC), so we do not know to what extent the positions we observe at the beginning of our sample were influenced by that event. It is a well-known fact that the initial reaction to the crisis in many countries was one of extreme caution, reflected in liquidity hoarding, and the situation in Chile was not different in that sense. Therefore it is possible that what we observe at the beginning is not a “normal” state of affairs, and what we observe over time is in part a reversal towards such a “normal” situation.

In addition, cross holdings of deposits suffered a boost by a public policy aimed at dealing with the consequences of the GFC. In effect, in July 2009, the Central Bank of Chile lowered the monetary policy rate (MPR) to 0.5%. To align financial asset prices with the monetary policy path, the Bank also established a Term Liquidity Facility (FLAP) for banks.<sup>27</sup> This facility lent against collateral at a fixed rate equal to the MPR, at 90 and 180 days. Among the accepted collateral were term deposits issued by a third bank. This may explain the increase in the size of interbank term deposit holdings depicted in Figure A.1. It is reasonable to venture that banks increased their investments in term deposits, as long as they could fund those positions at a very low rate (the MPR). In doing so, several of them increased the number of banks they invested in, which is consistent with an observed increase in out-degree (Figure A.2 (a)). This could explain the tendency towards the increase and strengthening of the core observed until mid-2010.

The facility was closed in May 2010. Up to the end of 2011, the system maintained these positions as a percentage of assets in the system, to begin reducing them gradually until the end of our period of analysis (Figure A.1). By the end of 2012 we observe an increase in the size of the core (Figure 6), while the number of links between banks slightly diminishes (Figure A.2 a and b). Therefore, the strengthening of the core comes from reallocation of links, rather than from an increase in the total number of them. The motivation for banks for doing this is stands beyond the scope of this paper.

## 6 Concluding remarks

In this paper we have developed a framework, based on Stochastic Blockmodelling, to characterize in an informative way the structure of a network with real data. This framework allows us to determine highly informative partitions of real-world financial networks in a parsimonious way. We find that a varied core-periphery structure – that is, one with, eventually, more than one core and

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<sup>27</sup> See Central Bank of Chile (2010), Box III.1.

different types of peripheries – can be observed in the interbank market analyzed in this paper. The method allows the data to speak for itself rather than contrasting it to stylized benchmarks. We also show that the method shows relevant facts that are impossible to infer from commonly used network metrics. Finally, we provide evidence that both the structure of interbank exposures and its evolution over time may differ substantially across instruments.

The method presented in this paper provides information that policymakers should take into account for financial stability analysis. It will help them in identifying different groups of banks that could be more or less vulnerable to shocks, as well as those more or less likely to generate shocks to the system. This information can be used to map systemic risks and exposures to them, allowing prioritizing monitoring accordingly. In addition, an assessment of the stance of systemic risk, along the lines of Cifuentes *et al* (2005) and Elliot *et al* (2014), is also possible.

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**Table 1:** Probability of interconnection between a pair of banks belonging to the same or different groups ( $K=3$ ).

(a) Term deposits

	Lender		
	First (6-11)	Second (4-9)	Third (5-9)
	First	Second	Third
	Borrower		
First	79%	86%	9%
Second	25%	30%	1%
Third	8%	10%	1%

(b) Derivatives

	Lender		
	First (9-15)	Second (3-9)	Third (4-6)
	First	Second	Third
	Borrower		
First	89%	79%	10%
Second	74%	15%	2%
Third	9%	2%	2%

**Source:** Authors' calculations.

**Note:** The position (A, B), where A indicates a row and B a column, is the probability of observing a loan from a bank in group B to a bank in group A. The probability shown corresponds to the 50<sup>th</sup> percentile of the probability calculated through the period 2009m1-2015m6. In parentheses the minimum and maximum number of banks in that group over all the period.

**Table 2:** Probability of interconnection between a pair of banks belonging to the same or different groups ( $K=4$ ).

(a) Term deposits

	Lender			
	First (6-10)	Second (2-8)	Third (4-7)	Fourth (4-7)
	First	82%	88%	43%
	Second	40%	28%	4%
	Third	44%	47%	7%
	Fourth	3%	3%	1%

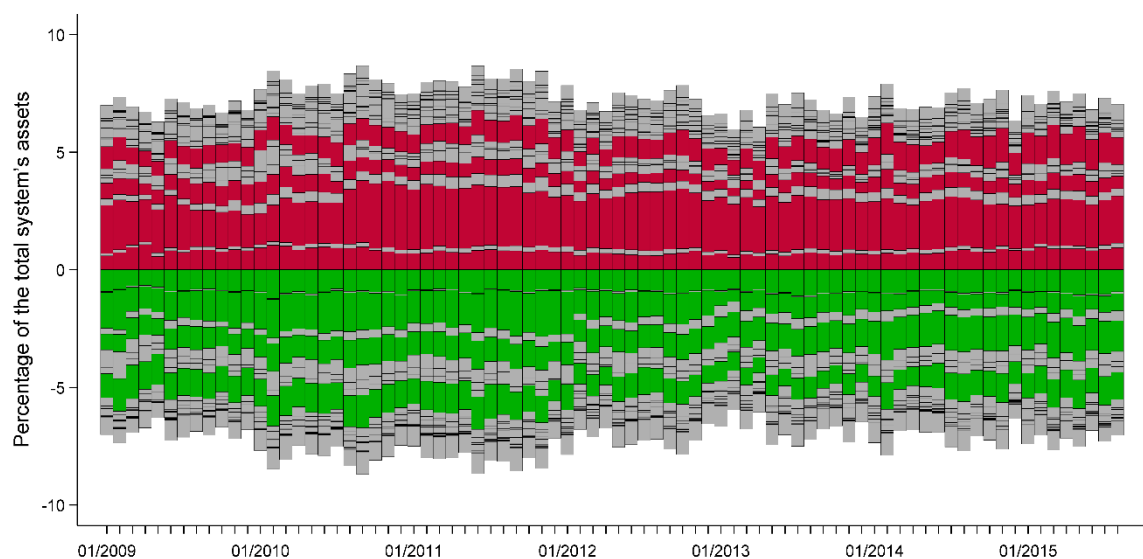
(b) Derivatives

	Lender			
	First (6-12)	Second (5-8)	Third (1-5)	Fourth (4-6)
	Fisrt	88%	95%	72%
	Second	94%	57%	27%
	Third	39%	18%	9%
	Fourth	5%	2%	3%

**Source:** Authors' calculations.

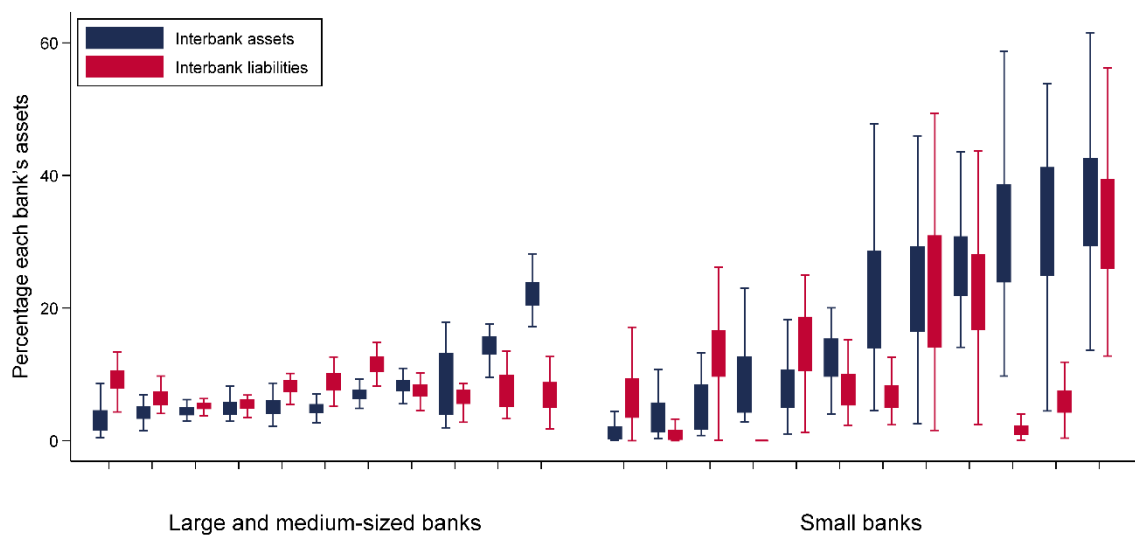
**Note:** The position (A, B), where A indicates a row and B a column, is the probability of observing a loan from a bank in group B to a bank in group A. The probability shown corresponds to the 50<sup>th</sup> percentile of the probability calculated through the period 2009m1-2015m6. In parentheses the minimum and maximum number of banks in that group over all the period.

**Figure 1:** Stock of interbank assets (positive side) and liabilities (negative) by bank.



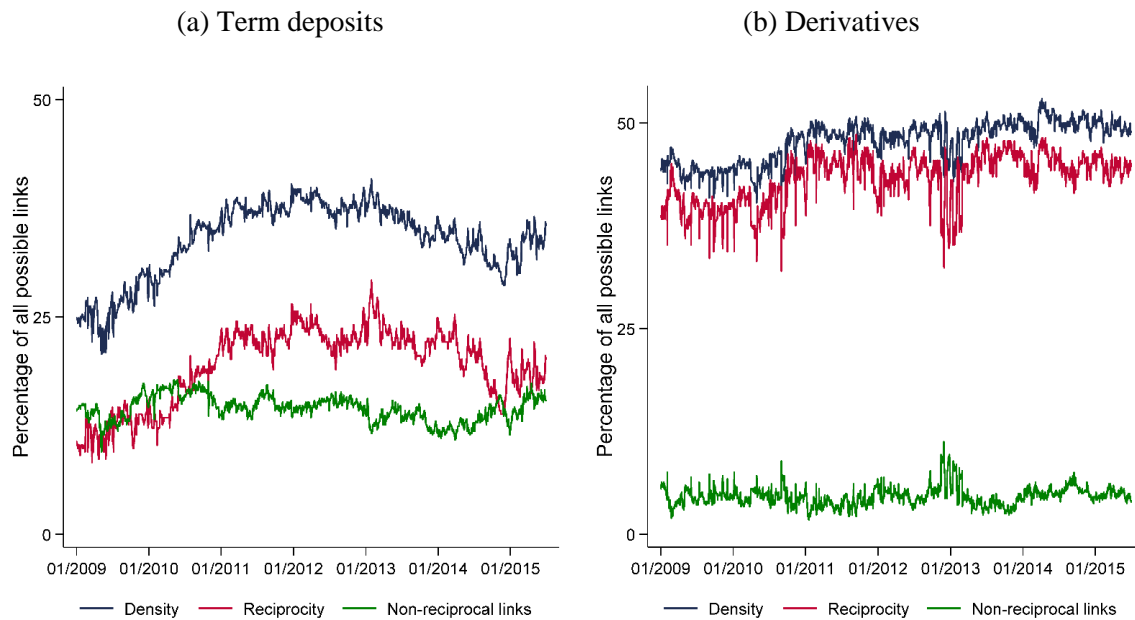
**Source:** Authors' calculations based on information of the Superintendency of Banks and Financial Institutions of Chile.  
**Notes:** The largest four banks are shown in color. Interbank exposures include interbank loans, current accounts, repo, derivatives, term deposits, bank bonds, interbank loans with collateral and operations in course of liquidation.

**Figure 2:** Distribution of interbank assets and interbank liabilities by bank.



**Source:** Authors' calculations based on information of the Superintendency of Banks and Financial Institutions of Chile.  
**Notes:** In order to preserve anonymity of banks, the banks are grouped into two categories: large- and medium-sized banks (11) and small banks (12). Boxes show the 5<sup>th</sup>, 25<sup>th</sup>, 75<sup>th</sup> and 95<sup>th</sup> percentiles of monthly ratios.

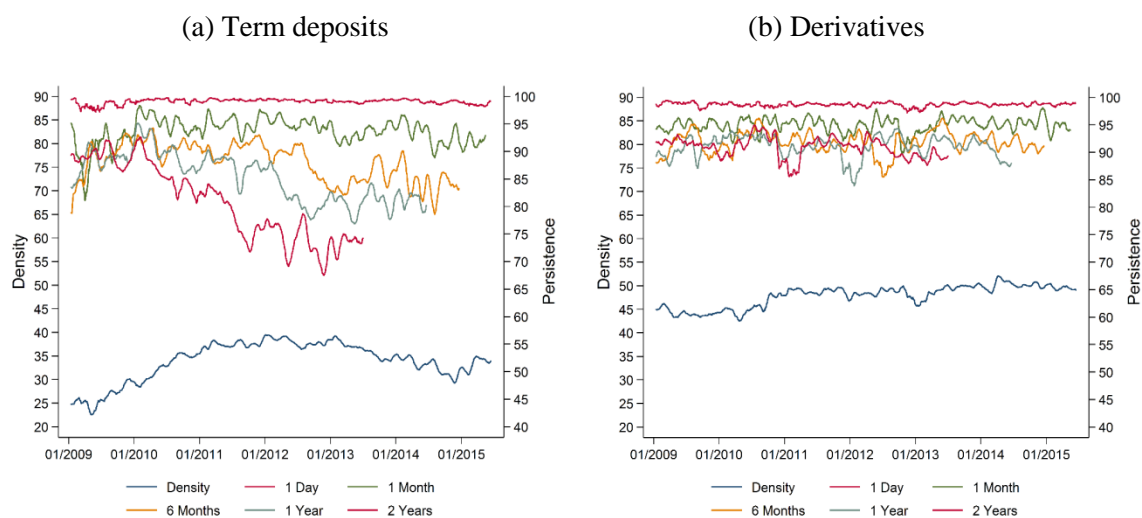
**Figure 3:** Density, reciprocity and non-reciprocal links.



**Source:** Authors' calculations.

**Notes:** Density is the percentage of links observed in the interbank market over the total links possible (506) given the number of banks (23). Reciprocity is the density when only reciprocal links (A lends to B and B lends to A) are considered. Daily frequency.

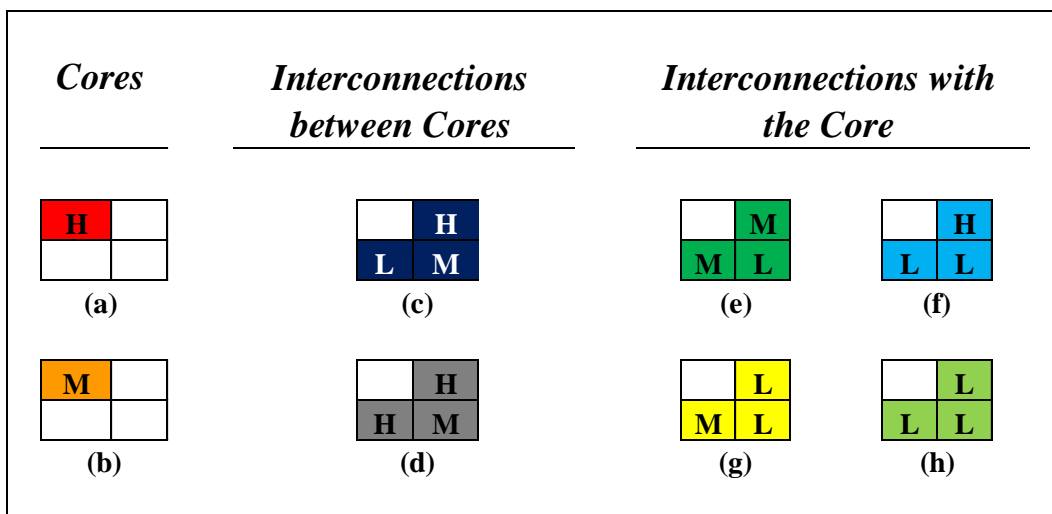
**Figure 4:** Density and persistence.



**Source:** Authors' calculations.

**Note:** Persistence shows for each date the percentage of existing links that will still exist after a given horizon. Daily frequency.

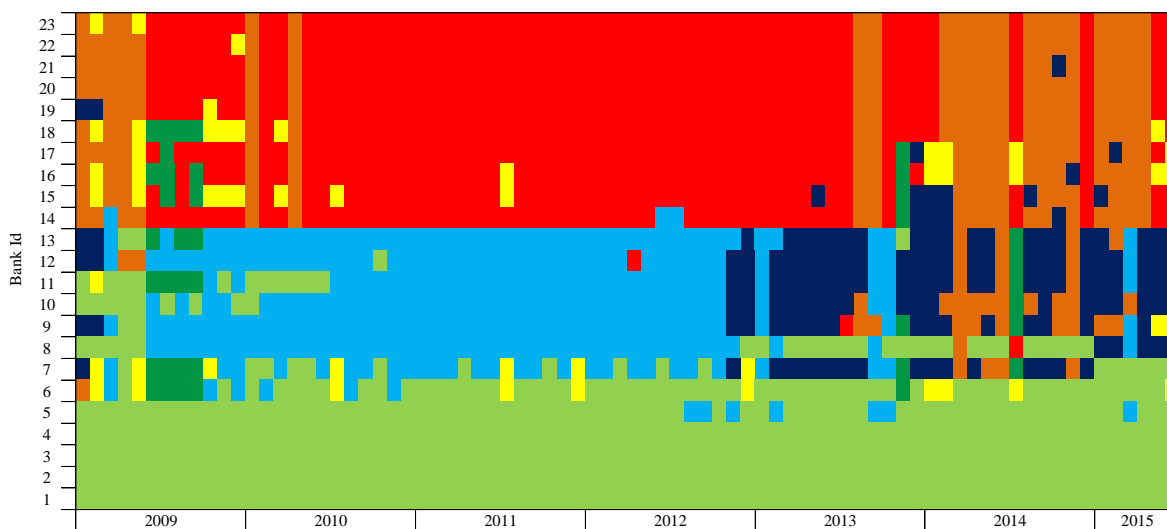
**Figure 5:** Patterns of interconnections among groups of banks.



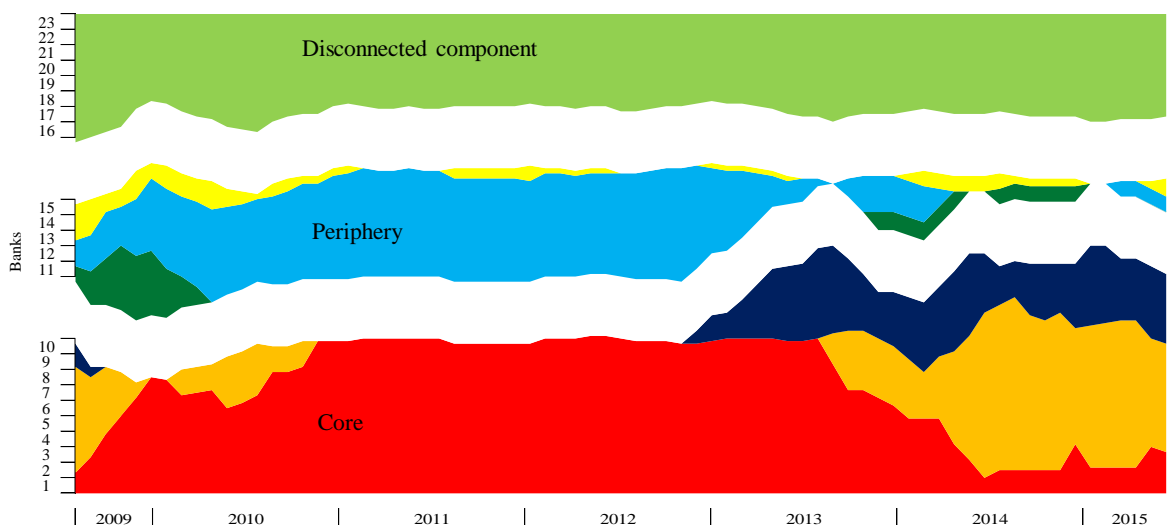
**Notes:** The letter H indicates a probability higher than 75%, the letter M indicates a probability between 40% and 75%, and the letter L indicates a probability lesser than 40%.

**Figure 6:** Term deposits. Group membership of banks.

(a) Timeline of group membership for individual banks (banks listed on axis Y)



(b) Timeline of group membership ordered by group (number of banks on axis Y)



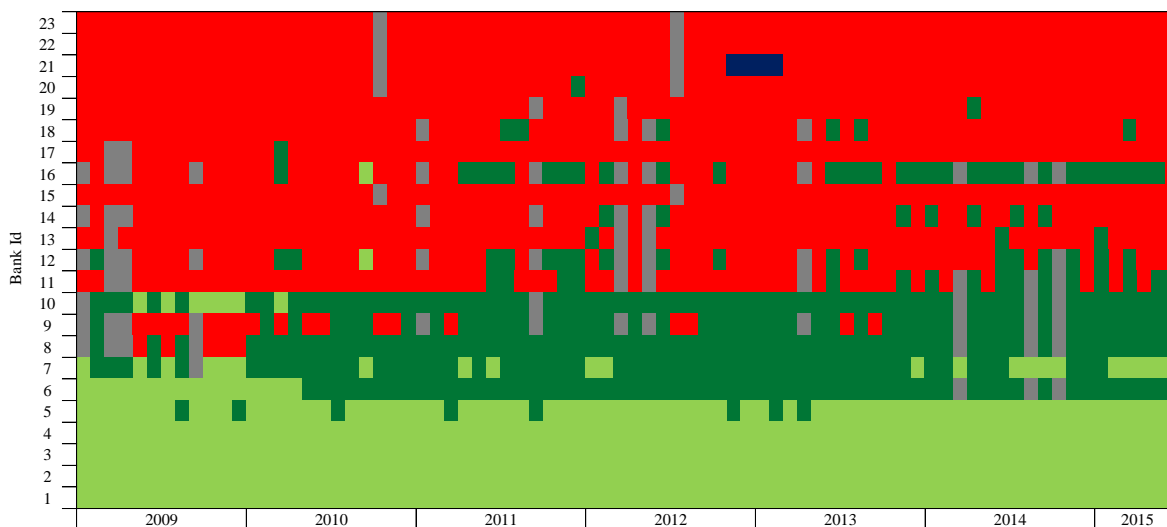
**Source:** Authors' calculations.

**Notes:** Colors identify the pattern of interconnections according to Figure 5. Since we use a 6-month moving average for graph (b), the first five months of the sample are not depicted. The first white area of the graph (b) (from bottom to top) separate the core (red, orange and dark blue) from the periphery (dark green, light blue and yellow) and the second separate the periphery from the disconnected component of the network (light green).

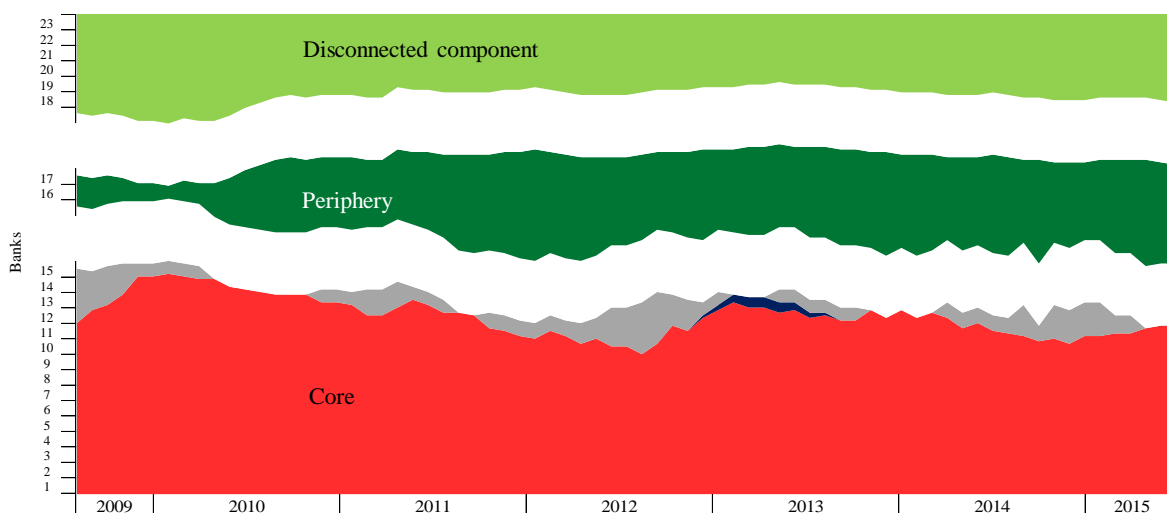


**Figure 7:** Derivatives. Group membership of banks.

(a) Timeline of group membership for individual banks (banks listed on axis Y)



(b) Timeline of the group's membership ordered by group (number of banks on axis Y)



**Source:** Authors' calculations.

**Notes:** Colors identify the pattern of interconnections according to Figure 5. Since we use a 6-month moving average for graph (b), the first five months of the sample are not depicted. The first white area of the graph (b) (from bottom to top) separates the core (red, orange and dark blue) from the periphery (dark green, light blue and yellow) and the second separates the periphery from the disconnected component of the network (light green).

## Appendix

**Table A.1:** Relative size of the eight instruments that comprise the Chilean interbank market.

No.	Instrument	Relative size (%)					
		Mean	p5	p25	p50	p75	p95
1	Term deposits	<b>64.0</b>	48.1	56.5	65.2	69.6	75.1
2	Derivatives	<b>15.3</b>	7.5	10.3	13.7	19.5	26.4
3	Payments outstanding	<b>14.0</b>	7.5	11.5	13.8	16.8	21.0
4	Bank bonds	<b>3.4</b>	2.0	2.5	3.2	4.5	5.4
5	Uncollateralized Interbank loans	<b>2.9</b>	0.7	1.6	2.7	3.8	7.2
6	Current accounts	<b>0.2</b>	0.1	0.1	0.2	0.3	0.4
7	Repo & securities lending	<b>0.1</b>	0.0	0.0	0.0	0.0	0.7
8	Interbank loans with collateral	<b>0.0</b>	0.0	0.0	0.0	0.0	0.0

**Note:** The detailed description in *Compendio de Normas Contables*, Chapter C-3, Circular No. 3.555 -02.10.2013.

**Table A.2:** Distribution of the interconnections density among group de banks.

**Panel A: Term deposits**

Group		Distribution					Mean	Max.	Min.	Sd.	No. of times that we observe this relationship*
Borrower	Lender	p5	p25	p50	p75	p95					
1	1	0.63	0.73	0.80	0.83	0.85	0.77	0.88	0.54	0.08	78
1	2	0.19	0.80	0.86	0.91	0.95	0.78	0.98	0.02	0.24	78
1	3	0.03	0.07	0.11	0.19	0.77	0.20	0.96	0.01	0.23	74
1	4	0.05	0.08	0.11	0.15	0.19	0.11	0.22	0.01	0.05	21
2	1	0.11	0.22	0.26	0.34	0.89	0.32	0.94	0.05	0.20	78
2	2	0.02	0.17	0.30	0.42	0.56	0.29	0.65	0.00	0.16	78
2	3	0.01	0.01	0.01	0.03	0.64	0.08	0.92	0.01	0.20	74
2	4	0.01	0.02	0.02	0.04	0.07	0.04	0.23	0.01	0.05	21
3	1	0.03	0.06	0.09	0.15	0.63	0.18	0.89	0.01	0.21	74
3	2	0.02	0.07	0.10	0.13	0.71	0.17	0.82	0.01	0.21	74
3	3	0.01	0.01	0.01	0.05	0.09	0.04	0.59	0.00	0.07	74
3	4	0.01	0.01	0.02	0.03	0.06	0.03	0.09	0.01	0.02	21
4	1	0.01	0.01	0.03	0.06	0.09	0.04	0.10	0.01	0.03	21
4	2	0.01	0.02	0.03	0.05	0.13	0.04	0.17	0.01	0.04	21
4	3	0.01	0.02	0.03	0.04	0.08	0.03	0.08	0.01	0.02	21
4	4	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.01	0.00	21

**Panel B: derivatives**

Group		Distribution					Mean	Max.	Min.	Sd.	No. of times that we observe this relationship*
Borrower	Lender	p5	p25	p50	p75	p95					
1	1	0.83	0.88	0.89	0.90	0.91	0.88	0.91	0.82	0.02	78
1	2	0.14	0.59	0.80	0.88	0.97	0.73	0.98	0.09	0.21	78
1	3	0.02	0.07	0.12	0.18	0.93	0.21	0.93	0.01	0.25	74
1	4	0.04	0.07	0.10	0.11	0.12	0.09	0.12	0.04	0.03	13
2	1	0.14	0.58	0.75	0.87	0.97	0.71	0.98	0.10	0.22	78
2	2	0.01	0.05	0.15	0.32	0.78	0.22	0.79	0.01	0.21	78
2	3	0.01	0.02	0.02	0.06	0.84	0.11	0.91	0.01	0.23	74
2	4	0.01	0.02	0.02	0.09	0.13	0.05	0.13	0.01	0.04	13

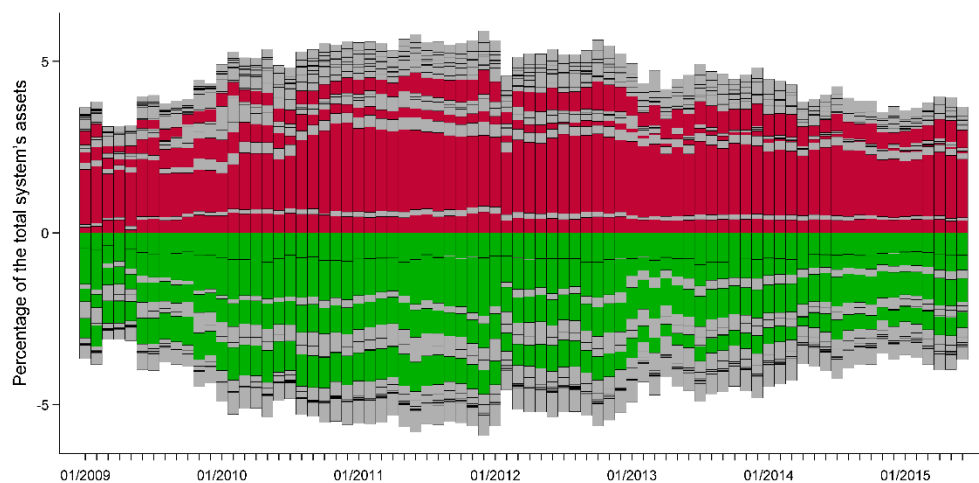
3	1	0.03	0.06	0.09	0.13	0.64	0.14	0.83	0.02	0.18	74
3	2	0.01	0.02	0.02	0.06	0.27	0.07	0.95	0.01	0.15	74
3	3	0.01	0.01	0.02	0.02	0.20	0.03	0.20	0.01	0.05	74
3	4	0.02	0.02	0.03	0.08	0.09	0.04	0.09	0.02	0.03	13
4	1	0.01	0.04	0.05	0.06	0.10	0.05	0.10	0.01	0.02	13
4	2	0.01	0.02	0.02	0.06	0.12	0.04	0.12	0.01	0.04	13
4	3	0.02	0.02	0.03	0.23	0.30	0.10	0.30	0.02	0.11	13
4	4	0.01	0.02	0.02	0.03	0.03	0.02	0.03	0.01	0.01	13

**Notes:** The maximum number of times that we can see one relationship is 78 (one per month). Data from 2009m1 to 2015m6.

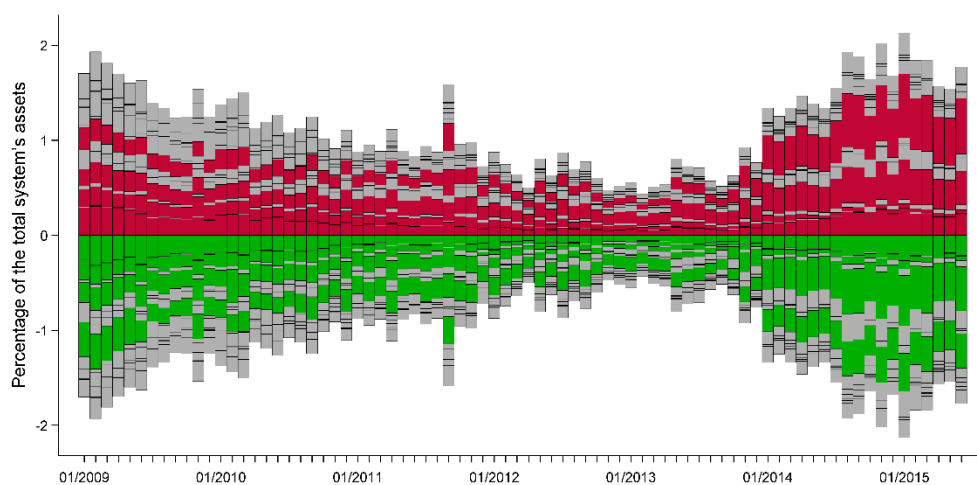
**Source:** Authors' calculations.

**Figure A.1:** Stock of interbank assets (positive side) and liabilities (negative) by bank.

a) Term deposits



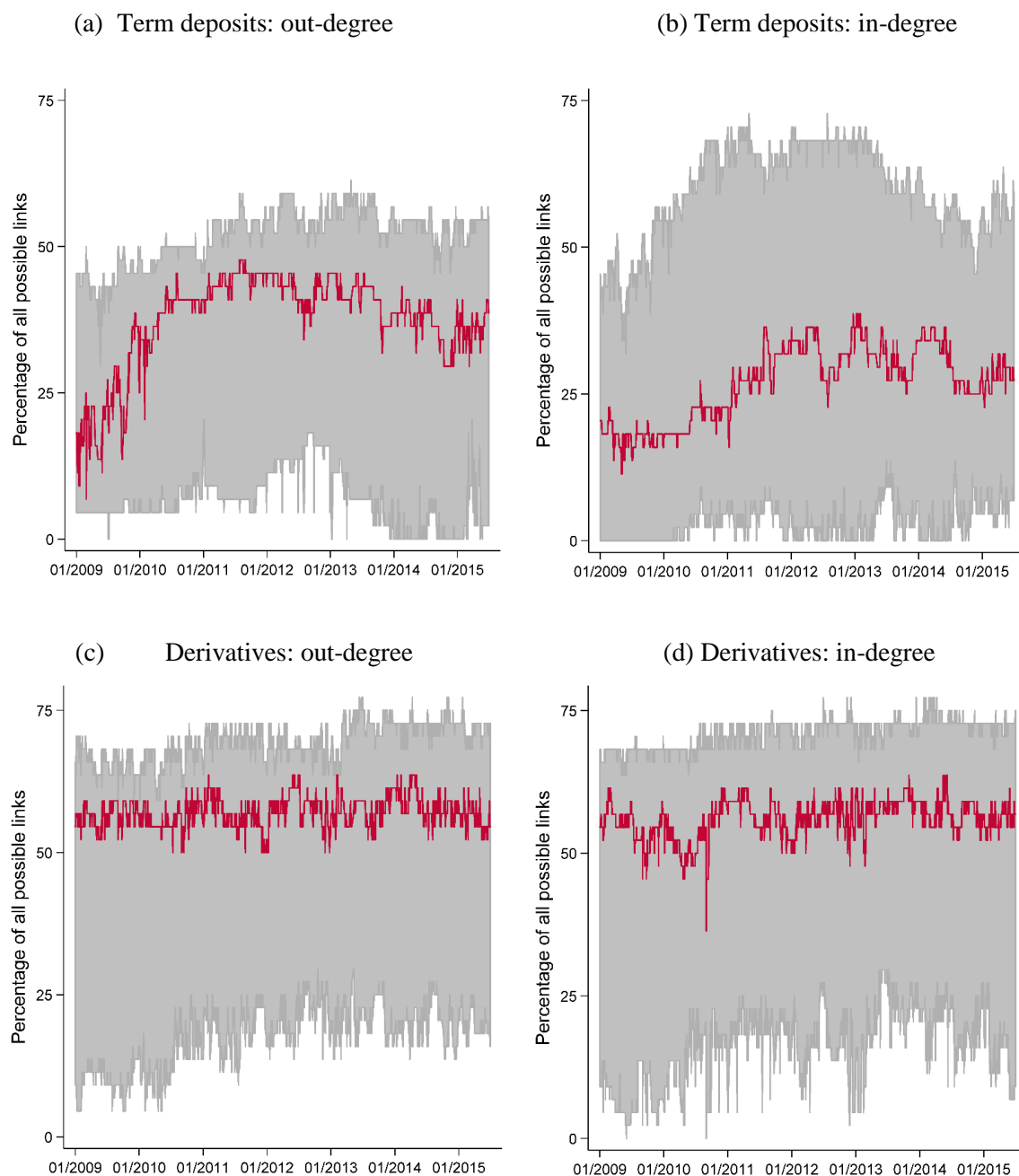
b) Derivatives



**Source:** SBIF and Central Bank of Chile.

**Notes:** The largest four banks are shown in color. Interbank exposures includes interbank loans, current accounts, repo, derivatives, term deposits, bank bonds, interbank loans with collateral and operations in course of liquidation.

**Figure A.2:** Daily in-degree and out-degree distribution.



**Source:** Authors' calculations.

**Note:** 50<sup>th</sup> percentile is the red line and 25<sup>th</sup> and 75<sup>th</sup> percentiles is gray area, daily frequency. In-degree is number of banks that lend to a given bank and out-degree is the number of counterparties that a given bank lends to.

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