BBVA Research

Creating Opportunities

N.º 20/08

Working paper

Network Topology of the Argentine Interbank Money Market

Federico D. Forte

May 2020

Creating Opportunities

Network Topology of the Argentine Interbank Money Market

Federico D. Forte[a]

Abstract

This paper provides the first empirical network analysis of the Argentine interbank money market, commonly known as call market, based on data from the Central Bank of Argentina (BCRA). Its main topological features are described applying graph theory, focusing on the unsecured overnight loans settled from 2003 to 2017. The network, where banks are the nodes and the operations between them represent the links, exhibits low density, as is usual in financial networks, and a higher reciprocity than comparable random graphs. It displays a short average distance and its clustering coefficient remains above that of a random network of equal size. Both indicators are in line with those reported for other interbank networks around the world. Furthermore, the network is prominently disassortative. Different node centrality measures are computed. It is found that a higher centrality enables a node to settle more convenient bilateral interest rates compared with the average market rate, identifying a statistical and economically significant effect by means of a regression analysis. The degree distributions fit better to a Lognormal distribution than to a Poisson or a Power Law. These results constitute a relevant input for systemic risk assessment and provide solid empirical foundations for future theoretical modelling and shock simulations.

Keywords: Network Analysis, Interbank Market, Systemic risk

JEL classification: D85, G21, G28

a: BBVA Research Argentina. The views expressed in this publication are those of the author and do not necessarily reflect the position of BBVA. I would like to thank Viktoriya Semeshenko, Marcos Dal Bianco, Daniel Heymann, Martín Zimmermann as well as seminar participants at Central Bank of Argentina, University of Buenos Aires, Universidad Nacional del Sur and at the III Interdisciplinary Workshop on Complex Systems (UBA/UDELAR) for helpful comments. E-mail: federico.forte@bbva.com.

1. Introduction

Financial entities exhibit a high degree of interdependence. They forge interlinkages via both sides of their balance sheets, which are essential for efficient financial intermediation. The financial crises of the nineties and, fundamentally, the 2007-09 global turmoil underscored the necessity of a more rigorous comprehension of the systemic risks associated with these interconnections among banks. Additionally, those events highlighted the central role played by interbank money markets for a correct functioning of financial systems and for the effectiveness of monetary policies.

In this context, the network analysis and graph theory provide an insightful methodology to elucidate both direct and indirect interrelationships that are continuously built between the multiple agents of financial systems. This approach allows us to better understand phenomena like financial contagion, network externalities, cascade failures, etc., which have been highly emphasized by recent literature specialized in financial stability (Bougheas & Kirman, 2014).

This paper examines the topological structure of the Argentine unsecured interbank money market, commonly known as call market, from the vantage perspective of network theory. Banks conduct the management of a portion of their short-term liquidity positions through this market. The average interest rate settled, known as call rate, embodies a fundamental reference of the “cost of money” in Argentina. This short-term rate is a key benchmark for the determination of other longer-term rates in the economy. For this reason, the call market represents one of the most direct transmission channels at disposal of the Central Bank of Argentina (BCRA) to implement its monetary policy. It is one of the main markets where the monetary authority exerts substantial influence and it is crucial for defining the monetary conditions of the whole economy, such as the interest rates levels and the evolution of monetary aggregates. Hence the importance of examining the structural features of the network of loans that arise from this market, in order to assess its stability and systemic risks.

Thus, the call market is represented as a network, where financial institutions are nodes and the overnight loans among them are links. The aim of this paper is to describe the structure of this network, from January 1st, 2003 to December 31st, 2017. Its main topological measures are analyzed to investigate if it shows similarities with stylized network models. This task enables us to draw conclusions, for instance, about its resilience to different types of disruptive events.

This document provides the first comprehensive network analysis of the Argentine interbank market. This line of empirical research has been growing extensively since the early 2000s, along with the development of computational technologies and a larger availability of data sets suitable for applying these methods and techniques. Similar studies were carried out on the money market networks of several countries, such as Italy (De Masi, Iori, & Caldarelli, 2006; Iori et al., 2008), U.S.A. (Bech & Atalay, 2008), or Switzerland (Schumacher, 2017), just to mention a couple of examples. A detailed Table displayed in the Appendix summarizes the main topological measures of other comparable interbank networks analyzed in the world using an analogous approach.

The time span of 15 years addressed in this paper for Argentina is one of the most extensive intervals examined so far, when compared with the existing empirical studies on financial networks. As a strategy to deal with such a long time period, and in pursuit of more clarity, we subdivided it into six different stages. This allows a better description of the variability experienced by the network structure throughout these years, which, to some extent, tended to move together with the macroeconomic volatility of Argentina’s economy.

The paper is organized as follows. The next section explains the main characteristics of the Argentine call market, the different monetary policy instruments and minimum liquidity requirements imposed by the BCRA, which impact directly on money markets (Subsection 2.1 details the different stages in which the time period studied is analytically subdivided). Section 3 briefly reviews the main concepts of network theory applied in the paper and the empirical literature on financial networks. Section 4 describes the database used. In Section 5, the methodological framework is thoroughly explained. The results are outlined in Section 6. Section 7 presents an econometric regression aimed at quantifying the effects derived from node centrality on the banks' capability for negotiating a more convenient interest rate in their individual transactions in the call market. Finally, Section 8 lists some concluding remarks, policy implications and lines of research for future work.

2. The Argentine interbank money market

The call market is the Argentine traditional interbank market in which banks negotiate their liquidity positions with each other. The daily weighted average interest rate of these transactions represents one of the most relevant short-term rates of the economy, as it is an essential reference for determining the other interest rates of the domestic financial system.

The loans in this market are unsecured and are agreed between entities by telephone trading. They define bilaterally the interest rate of the transaction. Only institutions authorized by the BCRA can operate in this market. The vast majority of the loans are overnight, although a few longer-term transactions also take place. Financial institutions make a risk assessment of each possible counterparty and then define specific credit lines for each one (mainly, they determine the limit amount of money to be granted). Hence, when an entity needs liquid funds, it resorts in the first place to those banks with which it has credit lines available. This gives rise to repeated interactions between pairs of agents in the market. Network analysis is an approach that, precisely, allows for a comprehensive examination of these relationships that emerge along time and helps us to elucidate the structure of interdependencies that arises from the liquidity trail within the interbank markets.

The bilateral transactions are compensated through the real-time gross settlement system called "MEP"[1]. The transfers of funds are not subjected to settlement risks because the monetary authority verifies, before the settlement of each loan, the existence of the corresponding funds in each account involved.

In Argentina, there is another complementary market in which the financial institutions can negotiate their liquidity positions, known as "REPO market". In contrast, this is a secured market and transactions are conducted through an electronic platform. This fact makes it more transparent compared with the call market, since all the participants are enabled to see the bids and offers of the rest. Nevertheless, to operate in the REPO market it is mandatory to fulfill several costly conditions, referred to the volume of assets and equity of the bank (among others), that are often impossible to meet by a significant number of entities[2]. This sort of barriers to entry explain, at least partially, the still substantial role played by the call market in the local financial system. Unfortunately, the necessary information to analyze the REPO market is not available yet, so this study will focus only on the call market.

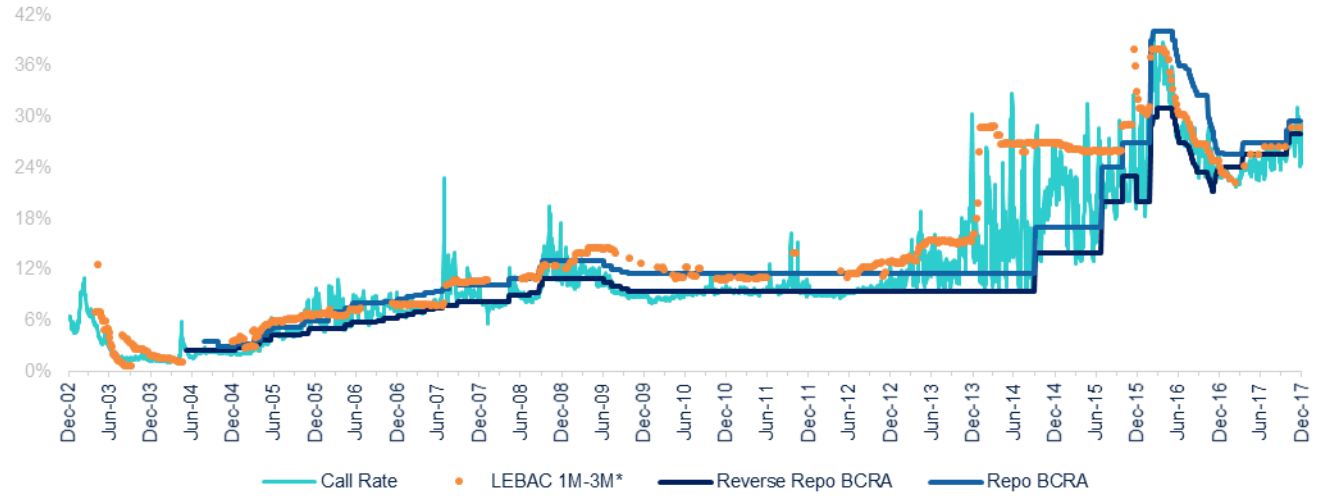
Due to the key role of the call rate as a benchmark for other interest rates in the economy, the BCRA has used several instruments to influence its behavior. Since 2002 (in a context of a public debt default), the monetary authority started to issue its own short- and middle-term securities, called LEBAC and NOBAC[3]. These securities were designed to absorb or provide liquidity from/to the market, affecting therefore the interest rates and monetary conditions of the economy. Additionally, since 2004, the BCRA began to operate actively in the REPO market, in

1: "MEP" stands for "*Medio Electrónico de Pagos*". It is the Real-Time Gross Settlement (RTGS) system administered by the BCRA, developed in 1997.
2: For example, in December 2017 only 58 financial entities were allowed to operate in the REPO market, out of a total of 77.
3: LEBACs were first issued on 13th March 2002 (by Comunicación "B" 7155 of the BCRA), and NOBACs on 2nd December 2003 (by Comunicación "B" 8064).

order to add complementary instruments to influence the liquidity conditions of the banks. A Central Bank's repo is a secured loan of liquid funds to a financial institution, while a reverse repo is the opposite transaction (a sort of "secured deposit" that banks make at the Central Bank). Usually, these loans have a maturity of 1 or 7 days.

In brief, since 2002 the BCRA has affected the liquidity conditions of the economy using mainly LEBAC, NOBAC and repos, trying to align the short-term interest rates with its policy objectives. Figure 1 shows the evolution of the call rate during these years, jointly with the interest rates of the BCRA's most relevant monetary policy instruments.

Figure 1. **Call rate and interest rates of monetary policy instruments** (annual %)



Source: BCRA. *Note: The Figure includes only the interest rates of the LEBACs with the shortest duration in each moment, provided that they are shorter than 105 days. Longer-term LEBACs are less relevant to explain the behavior of the call rate.

2.1. Macroeconomic context

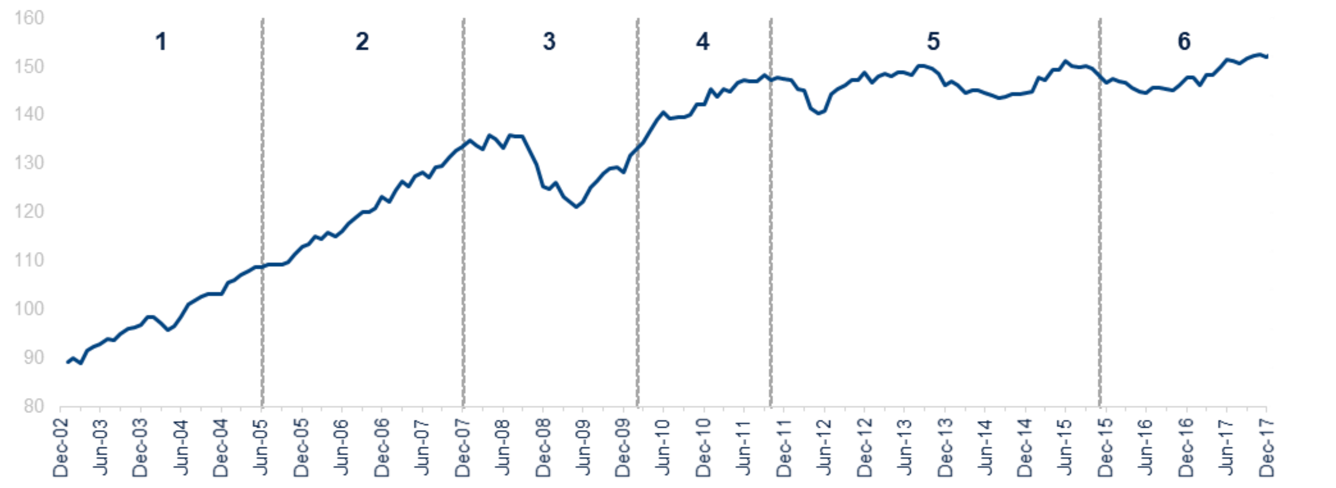
Money markets in Argentina have faced wide fluctuations during the years under analysis, along with the general macroeconomic volatility experienced by the country. For that reason, the time period studied in this paper is analytically subdivided into six different stages, defined according to the development of exogenous factors which affected crucially the interbank network in these years. This approach is useful to detect similarities, breaks and continuities in the evolution of its structural features over time.

The first stage comprises the lapse before the public debt restructuring, more precisely the months between January 2003 and June 2005. The economy was starting to recover from the deep crisis of 2001 and the financial system was facing many restrictions for its normal functioning, not only because of the widespread bank runs suffered the previous years, but also because of the sovereign debt default, which continually hindered local operations of many international financial entities. Within this first stage, the year 2003 is notably different from 2004, for two main reasons. In general terms, the economic situation of Argentina was considerably healthier during the latter, but the other relevant factor, more specific to the topics here analyzed, was that in 2004 the REPO market was established, which provided additional tools for managing liquidity to a still weakened domestic financial system.

Stage 2 is defined between July 2005 and December 2007, a period in which the economy was buoyant, after the debt restructuring and the surge of commodity prices (Figure 2). Then, Stage 3 is characterized by the outbreak of the global financial crisis in 2008 and its subsequent impact on Argentina, so it is delimited by the months between January 2008 and February 2010. During 2008 the economic activity started to decline, but the main impacts of the crisis were witnessed in the first half of 2009. It was not until the second half of that year that the economy began to rebound. The fourth stage is signaled by the marked recovery from the crisis, characterized by a strengthened economic activity together with the worsening of both fiscal and external deficits ("twin deficits"), so it is defined between March 2010 and October 2011.

By the end of October 2011, the government established harsh FX controls, introducing radical changes in regulatory frameworks, especially of the financial system. Capital mobility was strongly restricted and simultaneously many regulations were imposed on banks' interest rates. Gross Domestic Product (GDP) has stagnated since then, giving rise to a period of recurrent macroeconomic fluctuations, without the presence of a growing medium-term trend. The fifth stage is placed during these years, between November 2011 and November 2015. As a consequence of the aforementioned regulatory changes, the call rate's volatility exacerbated during that period (see Figure 1).

Figure 2. **Argentina Monthly Economic Activity Estimator* -EMAE-** (2004=100)



Source: INDEC. *Note: Seasonally adjusted index, 2004=100. The data of the year 2003 arise from a splice with the 1993 index

Since December 2015 until the end of the period covered in this paper, FX controls were completely relaxed and the regulations on active and passive interest rates were also liberalized. These last two years are included in the sixth stage. This lapse is characterized by the establishment of an Inflation Targeting regime, where the BCRA used a monetary policy interest rate as its main instrument to manage the monetary conditions of the economy. In this context, the call rate reduced drastically its volatility and progressively resumed a more similar behavior to the one displayed before 2012.

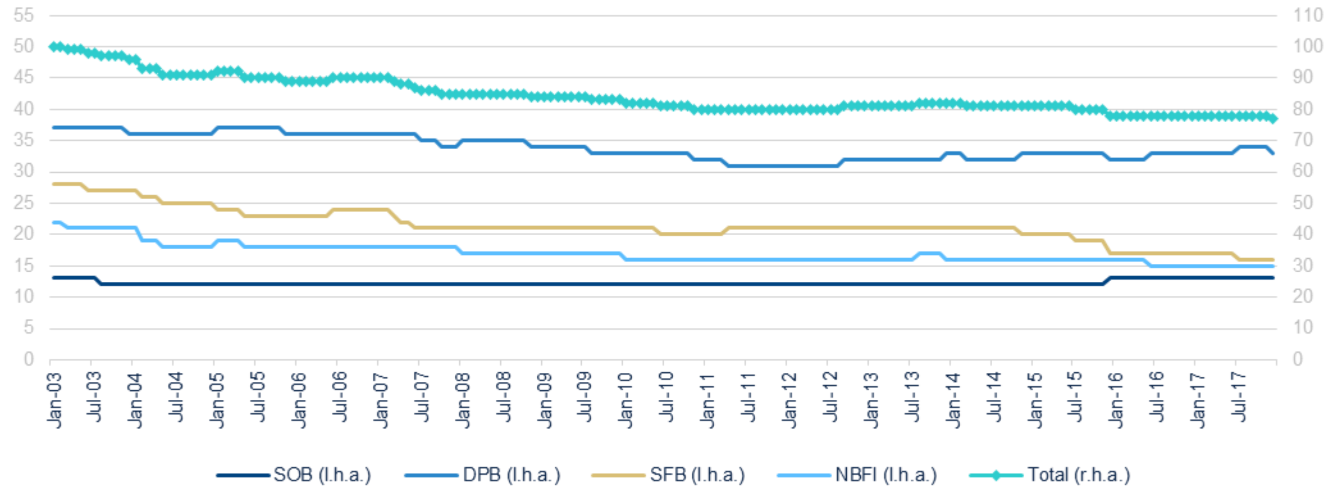
Table 1. **Analytical time stages**

Stage	Date	Main Events
1	January 2003 - June 2005	Debt default. Beginnings of economic recovery.
2	July 2005 - December 2007	Debt Restructuring. Economic dynamism.
3	January 2008 - February 2010	Global financial crisis.
4	March 2010 - October 2011	Macroeconomic recovery. Twin deficits widening.
5	November 2011 - November 2015	FX-market restrictions. Interest rate controls.
6	December 2015 - December 2017	FX-market and financial liberalization. Inflation Targeting Regime.

Source: INDEC. *Note: Seasonally adjusted index, 2004=100. The data of the year 2003 arise from a splice with the 1993 index

The number of financial entities decreased almost monotonically during the years under analysis. Starting from a total of 100 in January 2003, only 77 were active in December 2017 (Figure 3). We employ a usual classification in the domestic financial system to study the dynamics of different types of banks in the network. It divides them into four subgroups, according to the owner of the institution: State-Owned Banks (SOBs), Domestic Private Banks (DPBs), Subsidiaries of Foreign Banks (SFBs) and Non-Bank Financial Institutions (NBFIs). This classification, based on the structure and ownership of the equity of the institutions, is also useful as a proxy for the specific type of financial businesses in which each entity is specialized.

Figure 3. **Number of entities in the financial system, by type**



Source: BCRA

The decrease in the number of entities is verified for all the subgroups. SFBs were the group that declined the most, going from 28 entities in 2003 to 16 in 2017. NBFIs also experienced a notorious reduction (from 22 to 15). Meanwhile, DPBs and SOBs showed a more stable evolution, given that the former group only fell from a total of 37 to 33 banks, and the latter remained between 12 and 13 entities during the whole period. Some mergers, entries and exits of players took place during the 15-year period studied (these events cannot be fully visualized in Figure 3), but the description of those detailed facts is beyond the scope of this paper.

2.2. Minimum liquidity reserves

The minimum liquidity requirements imposed by the BCRA affect crucially the interbank money market, both directly and indirectly. In Argentina, during the period under analysis, they were defined according to the contemporary deposits of each entity, with different requirement coefficients depending on their maturity. Liquidity reserves are computed as the monthly average amount of money deposited by the banks in their Current Accounts (CA) at the BCRA. From 2003 to 2017, these requirements averaged 14% of total deposits, varying between 11% and 17% (taking into consideration all kinds of domestic currency deposits together).

At the end of each month, the monthly average of banks' current account balances at the BCRA must exceed these minimum levels to avoid financial penalties. Additionally, since 1997, a daily liquidity minimum has also been required, defined as a proportion of the requirement of the previous month (most of the time it was 50%), which entities must comply with at the end of each day.

The liquidity requirements cause substantial impact on the dynamics of interbank markets, since the banks tend precisely to resort to these markets to adjust their liquidity excesses or shortages, always considering the constraints imposed by the monetary authority.

3. Network theory and empirical interbank markets

The 2008 global financial crisis demonstrated the huge social costs and externalities that can arise from a systemic failure. For this reason, during the last decade, academic researchers as well as policy-makers have devoted a good deal of attention to issues associated with the stability and vulnerability of financial systems taking account of its interconnectedness (FSB-IMF-BIS, 2009). In this context, network theory is an advantageous framework to address comprehensively the complex interconnections among financial institutions (Haldane, 2009).

There is no clear consensus on whether a completely interconnected financial network reduces contagion and domino effects (Allen & Gale, 2000; Freixas, Parigi, & Rochet, 2000) or fuels them (Battiston *et al.*, 2012). Interconnectedness among banks improves risk diversification, but at the same time it makes them more prone to contagion. In any case, from a financial stability perspective, there is broad agreement on the idea that banks should neither be *too-big-to-fail* nor *too-interconnected-to-fail* (Hüser, 2015), as these types of institutions entail a potentially dangerous source of vulnerability to the whole system.

Section 3.1 reviews the main theoretical and methodological concepts of network theory applied in this paper. Section 3.2 compiles the empirical studies which examined the topological features of real interbank networks over the world with an analogous approach.

3.1. Network analysis and graph theory

Literature based on network theory has been growing exponentially for many years, both in theoretical and empirical terms. It was enriched by contributions from multiple sciences and disciplines, from sociology and psychology, to mathematics and physics (Granovetter, 1973; Lozares, 1996; Wasserman & Faust, 1994).

Specifically, a network (or graph) consists of a set of agents, called “nodes” (or “vertices”), that establish different kinds of relationships among them, known as “edges” (or “arcs”). Network analysis allows us to deal with complex structures of edges and nodes in a comprehensive way, that would otherwise be extremely difficult to approach analytically.

Some of the most prominent stylized network structures in theoretical literature can be understood and classified according to three main concepts (Albert & Barabási, 2002). The first one is the *distance* between every pair of nodes. It is defined as the number of edges along the shortest path connecting them. The second concept is the *clustering coefficient*. It indicates the probability that two nodes (both connected to a third vertex) have a link between themselves. In other words, it quantifies the density of triangles in the graph. The third element is the *degree distribution* of the graph. The "degree" of a node reflects its number of edges, and, in fact, it is unusual that all the nodes of a network have the same degree. The degree distribution of the different nodes in a network can be characterized by a distribution function, $P(k)$, which gives the probability that a randomly selected node has exactly k edges.

Graph theory was largely focused on *regular networks* until the 1950's. The general model was developed by the German physicist Ernst Ising (1925) and it was based on a fixed number of nodes connected to the *x* nearer neighbors, where *x* was in general a fixed number equal for all the agents in the graph. But since the 1950's, it has become more frequent to deal with big networks with no apparent behavior patterns, which were described as *random graphs*. Erdös and Rényi (1959) characterized formally the creation mechanism and properties of this kind of networks. In their model, given a fixed number of nodes, each pair is connected with a probability *p*. As *p* increases, the graph becomes more complete. Its average shortest distances are considerably shorter than in regular networks, its clustering is smaller, and its degree distribution approaches a Poisson.

More recently, Watts and Strogatz (1998) introduced the *small world networks*, based on the fact that, despite the often large scale of many networks, most of them showed relatively short distances among their nodes. Formally, the peculiar feature of these networks is that, given an equal number of nodes, they exhibit a similar average distance to that of random graphs, but their clustering coefficient is significantly higher.

Almost contemporaneously, Barabási and Albert (1999) developed the concept of *scale-free networks*, studying the degree distributions of various empirical networks. In random graphs, most of the nodes have a similar degree, around the mean of the distribution. But the authors pointed out that real networks hardly ever show this property. They verified that in many contexts their degree distributions followed a Power Law. Mathematically, a quantity k obeys a Power Law if it is drawn from a Probability Density Function (PDF) of the following form:

$$P(k) \propto k^{-\alpha}$$

where α is a constant parameter known as the *exponent* or *scaling parameter*. The most remarkable feature of this distribution is that it frequently originates extreme values very far from the mean, exhibiting heavier tails than Poisson, normal or exponential distributions (which had often been used in previous theoretical models). This gives rise to the possibility of networks in which few highly interconnected nodes coexist with many low-connected nodes. As a result, this kind of distribution implies that, with high probability, there exists a little group of nodes with disproportionate centrality and systemic importance in the network, linked with many others much more peripheral.

In general, their average distance is a little shorter than that of random networks. But in both cases, when the number of nodes in the graph grows, their distances increase approximately at the same pace (Albert & Barabási, 2002). Additionally, scale-free networks often display a higher clustering coefficient (between two and five times higher), although they never reach the magnitudes that are usually registered in small world networks.

Complementarily, Albert, Jeong, and Barabási (2000) proved that scale-free networks are *robust-yet-fragile* structures. They exhibit a surprising degree of tolerance against random errors, that is, they are very resilient to random failures or removals of a relatively large number of nodes (*robustness*). However, this error tolerance is coupled with a high susceptibility to targeted attacks. These networks break rapidly into isolated fragments when a few of the most connected nodes are removed (*vulnerability*). This attribute has critical implications regarding the assessment of systemic fragility of interbank networks. If a financial network displays this behavior, then a rigorous identification of the central agents becomes a priority task for central banks and regulators who have the responsibility of assuring financial stability.

Instead, random graphs show the converse risk structure. They easily absorb targeted attacks but tend to fall apart swiftly when random failures occur. This happens because those graphs do not have particularly central nodes of systemic relevance.

In practical terms, the most crucial consequences of the Power Law distribution derive from the fact that it is fat-tailed, in comparison with Poisson or Gaussian distributions. This makes the existence of extremely unusual cases more common, which in the context of interbank networks should be carefully considered by macro-financial policy-makers.

A note of caution is in order when trying to detect Power Laws in financial networks. Scale-free properties tend to emerge in the context of large graphs, but interbank networks are usually rather small (compared with social or biological ones, for example). This makes it troublesome to elucidate if a set of observations fits properly with one distribution or another, with serious risks of facing finite-sample biases (Clauset, Shalizi, & Newman, 2009). Taking that issue into account, many recent empirical and theoretical papers focused simply on the task of detecting "heavy-tailed behaviors". They test fits with other types of fat-tailed distributions in addition to Power Laws, not limiting themselves just to that latter alternative. These distributions show histograms with a slower decay than that of an exponential distribution as the variable of interest increases (in our case, the node degree):

$$\lim_{x \to \infty} \frac{f(x)}{e^{-x}} \neq 0$$

On that basis, other heavy-tailed distributions fitted in empirical literature were, for instance, the Lognormal distribution (e.g., Sala *et al.*, 2011), or the Weibull distribution (Kobayashi & Takaguchi, 2017). The main objective consists, therefore, in defining whether the degree distribution fits reasonably well with a Poisson (in which case the underlying network would be similar to a random graph) or if it displays statistically heavier tails (this would entail that it shows features closer to a scale-free network).

3.2. Empirical literature on interbank networks

The earlier empirical papers on this strand of literature focused on simulating shocks and failures on interbank networks of balance sheet exposures, with the specific aim of assessing the strength of contagion channels and the resilience of the graph. The most eminent pioneer studies were those of Furfine (1999a, 1999b) for the United States and Wells (2002) for the UK, but analogous analyses were also carried out for Switzerland (Sheldon & Maurer, 1998), Sweden (Blåvarg & Nimander, 2002), Germany (Upper & Worms, 2002) and Belgium (Degryse & Nguyen, 2004).

Boss *et al.* (2004), for Austria, and Inaoka *et al.* (2004), for Japan, carried out the first topological analyses of real interbank networks comparable with the one proposed in this paper. Thereafter, a vast proliferation of this type of analyses took place. A detailed Table in the Appendix summarizes the main results of 27 empirical studies on interbank networks around the world (for 18 countries, including the topological indicators presented here for Argentina).

Overall, real-world interbank networks are sparse, which means that they are far from complete, as only a small fraction of all possible edges actually materializes. In almost all empirical cases the average reciprocity is higher than the density of the network, so the connections tend to be more reciprocal than in random graphs. This fact denotes that financial institutions prefer to interact with those agents with whom they have already established relationships in the past. Hence the relevance of taking into consideration the presence of stable interconnections when assessing and modelling the behavior of financial entities.

Furthermore, interbank networks exhibit clustering coefficients higher than random graphs of the same size, but substantially lower than regular networks. They also display, in general, very short distances (between 1.5 and 4, on average). Thus, these structures can usually be characterized as small world networks.

Absolutely all the pieces of research reviewed conclude that interbank networks show disassortative mixing, which means that nodes with many edges tend to be connected to nodes with relatively less links, and vice versa.

There is consensus that financial networks follow heavy-tailed distributions. Many of the studies cited in the Appendix ascertain that degree distributions fit reasonably well to a Power Law (with an exponent between 2 and 3.5), which means that these networks could be described as scale-free. Consequently, it is usual to find few banks with an extraordinarily high number of edges, coupled with a myriad of nodes far less interconnected. It is worth mentioning that the number of participants in financial networks tends to be comparatively low (for example, much smaller than those in biological or social networks), which complicates dramatically the statistical analysis of their degree distributions.

Depending on the specific type of data analyzed, three different subgroups of financial networks can be clearly identified across literature: 1) balance sheet exposures; 2) payments; and 3) transactions in the interbank money markets. This paper is focused on the latter. This kind of networks is usually smaller than payment networks and is, on average, the sparsest among the three subgroups. In addition, they exhibit significantly lower clustering coefficients than payment systems, given that in general their values do not exceed 0.2, while in the second case the average clustering is around 0.5. The networks based on balance sheet exposures also show clustering coefficients slightly smaller than payment systems.

Particularly, research about the Argentine call market is scarce. One of the most relevant recent papers was written by Anastasi, Elosegui, and Sangiácomo (2010). They studied the effects derived from some characteristics of individual entities on the interest rate that they are able to negotiate in the market, applying econometric methods for panel data. They concluded that the banks' ownership and the size of their assets affect significantly the interest rate at which they obtain or provide funds, as well as their liquidity and the concentration on the supply or demand side of the market.

4. Data

The BCRA stores daily data about all the transactions carried out in the call market. The information available includes the lender and the borrower entities, the amount of money, the loan period, the currency involved, the interest rate settled and the type of rate (fixed or variable). Our sample consists of 314,188 loan operations, conducted between January 2nd, 2003 and December 29th, 2017, by 99 different entities (12 SOBs, 41 DPBs, 27 SFBs and 19 NBFIs). 99.3% of the transactions were settled in Argentine pesos and 88.8% were overnight.

With the aim of getting comparable results to those of other empirical studies on financial networks over the world, for most of this paper the sample is restricted to consider only the overnight loans in pesos with fixed interest rate. This subset comprises 278,497 operations (88.6% of the entire dataset).

For the construction of weighted networks, all the weights involved are based on amounts of money expressed in millions of constant pesos of 2017, that is, in real terms (constant purchasing power)[4]. The data on total deposits, assets and liquidity of financial institutions (used in the regressions of Section 7) emerge from information collected by the BCRA.

5. Notation, measures and methods

The topological measures of a network are indicators that describe its structural properties. The study of network topology and its evolution over time are very useful to elucidate the features of the complex set of interconnections and interdependencies that arise among the multiple participating agents.

Since the minimum liquidity requirement established by the BCRA for banks is based on the average amount of reserves deposited by them over the whole month, the monthly networks appear to be a better approximation of the genuine lattice of relationships among banks emerging from their liquidity management than the daily networks. In other words, as that regulation has a direct impact on the call market, the networks which arise on average during the whole month reflect more appropriately the structure of interactions established by the financial institutions to negotiate their liquidity excesses or deficiencies. Daily networks display an inherently higher level of volatility (already high in Argentina for any frequency), which complicates the examination of actual interconnections, without adding substantial analytical insights. Accordingly, Finger, Fricke, and Lux (2013), while investigating the Italian interbank network, emphasized that the daily networks could not be considered as being representative for the underlying “latent” network, as they often seemed to be random, but for longer aggregation periods the graphs actually contained significant non-random structure.

Hence, this paper will focus on the examination of monthly networks. This approach can also be understood noting that all the transactions in the call market are based on the previous existence of open credit lines among banks, which set up a “latent” network of interrelationships. Every day, some links “activate” and others do not, but they remain available in case of need. For these reasons, daily networks may be insufficient to account for the relevant structure of interconnections in the interbank market.

5.1. Network size and representation

The two most basic topological properties of a network are the number of nodes or vertices (N), which represent the participating agents, and the number of links that exist between them (M). In our monthly networks, each node

4: To this purpose, the Consumer Price Index (CPI) issued by INDEC (corresponding to Gran Buenos Aires) was applied for the period between January 2003 and November 2006 and for the months between May 2016 and December 2017. For methodological reasons, other sources were used for the remaining months. We used an average of the CPIs issued by provincial statistical institutes from December 2006 to April 2011, the CPI computed by the National Congress from May 2011 to July 2012, and the CPI issued by the Statistical Institute of the City of Buenos Aires from August 2012 to April 2016. Those multiple sources are the most reliable indicators available in each moment.

represents a bank that carried out at least one transaction in the call market during the month in question, while the edges are created when at least one operation was settled between a pair of entities during such lapse. These indicators provide a first description of both the size of the network and the density of its interconnections. They are also useful to estimate other topological measures and are utilized to calculate the computational complexity of the algorithms required to perform particular simulations.

In addition to the typical visual representation of graphs (advantageous because of its clarity and for exploratory purposes), there exists a matrix representation. That approach is crucial to deal formally with such structures and to implement algorithms based on them. This type of representation is known as Adjacency Matrix, a $N \times N$ matrix (denoted by "A"), whose components, a_{ij}, are defined as follows:

$$a_{ij} = \begin{cases} 1 & if \ |w_{ij}| > threshold \\ 0 & \qquad otherwise \end{cases}$$

Where w_{ij} is the average amount of money traded during the month between the bank i and the bank j. In our case, we set the minimum threshold at zero. It is worth recalling that the amounts of pesos involved are always expressed in constant purchasing power.

In other words, each component of the matrix A is defined depending on whether at least one interbank loan was settled or not between each pair of i and j financial institutions during the month. For most of this paper, we will focus on the directed networks. It implies that a_{ij} and a_{ji} are not necessarily equal, thus the matrix may not be symmetric. The direction of the flows of money (i.e., if they are being borrowed or lent by a specific bank) is relevant to describe the type of edges involved. Therefore, a link is incoming to the borrower and outgoing from the lender of the funds.

Another type of matrix is the so-called Weighted Adjacency Matrix (denoted by "W"), whose components, w_{ij}, are the average amount of constant pesos negotiated by each pair of banks during the month. Weighted graphs are useful to take into account the importance of each edge relative to the others, given that a link which involves large amounts of money is not equivalent to other that canalizes relatively smaller sums.

The *average distance* and the *diameter* of a network are two additional measures related to the size of the graph, which simultaneously consider its level of interconnectedness. The distance[5] (d_{ij}) between two nodes i and j is defined as the number of edges along the shortest path connecting them. Thus, the average shortest distance (L) is the arithmetic mean of all the distances in the network:

$$L = \frac{1}{N(N-1)} \sum_{i,j;i \neq j} d_{ij}$$

It indicates how "close", on average, are the agents to each other[6]. In turn, the longest distance between the nodes in the network is known as the "diameter" of the graph. Among the different algorithms developed to compute these indicators, the most frequently used is the one designed by Dijkstra (1959), which is applied in this paper.

5: Also called "geodesic distance".
6: In the case of disconnected networks (i.e., there exists at least a subset of nodes which is not linked at all with the rest), it is usually considered the average distance of the biggest subset of connected nodes.

5.2. Connectivity

The “density” or “degree of completeness” (δ) of a network is a measure that quantifies the percentage of the potential links that actually exist, given the number of nodes of the graph:

$$\delta = \frac{\sum_{ij} a_{ij}}{N(N-1)}$$

This indicator ranges from zero (for a set of nodes with no edges) to 1 (in which case the network is “complete”, as it is fully connected). Technically, the stylized network with the minimum degree of completeness is the so-called “tree network”, where all nodes are connected by exactly one path, and it has a density equal to 1 divided by the number of nodes. As aforementioned, real-world interbank networks tend to display low density.

For directed graphs, it is often relevant to know if their edges are reciprocal, i.e., to find out to what extent the links that go from node i to node j are also directed in the opposite way, that is, from j to i. The standard measure of the “reciprocity” (R) in a network is the following:

$$R = \frac{\sum_{ij} a_{ij} a_{ji}}{M}$$

However, a flaw of this indicator is that it does not take account of the fact that denser networks tend to have, consequently, a higher number of reciprocal links, due exclusively to random reasons (Costa *et al.*, 2007). An alternative way to address this issue is adjusting R for the degree of completeness of the network under consideration:

$$R\ adjusted = \frac{\sum_{ij}(a_{ij}-\delta)(a_{ji}-\delta)}{\sum_{ij}(a_{ij}-\delta)^2} = \frac{R-\delta}{1-\delta}$$

Values of this indicator above zero imply a larger reciprocity than a random network with the same density, while values below zero suggest a smaller level of reciprocity than it would be expected in a random context. The former case is known as a “reciprocal” network, and the latter as an “anti-reciprocal” one. These measures are very useful for evaluating the type of relationships and interdependences that emerge in financial systems.

A simple but fundamental concept in network theory is the “degree” of a node. This indicator captures the number of nodes that a specific node is connected to. Hence, the degree (k_i) of a vertex i is defined, for the case of an undirected network, as:

$$k_i = \sum_{j \in N(i)} a_{ij}$$

Where $N(i)$ is the set of neighbors of vertex i; that is, the set of nodes that have an edge (in any direction) with vertex i. In the case of directed graphs, the notions of in-degree (k_i^{in}) and out-degree (k_i^{out}) become relevant. k_i^{in} stands for the number of nodes with which node i has incoming edges (in the context of this paper, the number of banks from which a bank i has borrowed funds), while k_i^{out} is the number of nodes with which node i possesses outgoing links (i.e., the quantity of banks to which bank i has lent money):

$$k_i^{in} = \sum_{j \in N(i)} a_{ji} \;\; ; \; k_i^{out} = \sum_{j \in N(i)} a_{ij}$$

The average degree of a network is the arithmetic mean of its nodes' degrees, and it constitutes a key measure of the connectivity among the participants of the system. The average out-degree and in-degree of monthly networks are computed similarly (by the arithmetic mean of k_i^{out} and k_i^{in} for all i, respectively).

An associated indicator is the node strength (s_i). It is the sum of the weights of all the edges of a node; that is, the sum of the amounts of money involved in all the links of vertex i:

$$s_i = \sum_{j \in N(i)} (w_{ij} + w_{ji})$$

The strength of a node can be interpreted as a measure of the intensity of its interactions, and not just as an absolute level of connectivity (as is the case of the degree). It is convenient to assess in a different way the relevance of the entities that operate large amounts of money per month, with respect to the entities that may be connected to many others (i.e., display a high degree) but through low-value operations. The in-strength (s_i^{in}) and the out-strength (s_i^{out}) of the nodes will be analogously computed, but weighting the edges only by the funds borrowed or granted, respectively:

$$s_i^{in} = \sum_{j \in N(i)} w_{ji} \;\; ; \; s_i^{out} = \sum_{j \in N(i)} w_{ij}$$

Another key topological feature is the assortative mixing, or assortativity, of the nodes in the graph (ρ_{kj}). It refers to the preference of the nodes between the option of being connected with others of a similar degree to one's own or relating to a greater extent with those that exhibit a different degree. Many ways to compute this indicator were developed, but we use the Pearson correlation coefficient between the degrees of nodes that share links, in line with Newman (2002), one of the seminal contributions regarding this matter:

$$\rho_{kj} = \frac{M^{-1}\sum_l k_l j_l - \left[M^{-1}\sum_l \frac{1}{2}(k_l + j_l)\right]^2}{M^{-1}\sum_l \frac{1}{2}(k_l^2 + j_l^2) - \left[M^{-1}\sum_l \frac{1}{2}(k_l + j_l)\right]^2}$$

Where k_l and j_l are the degrees of the vertices at the ends of the lth edge, with l = 1, …, M. The assortativity coefficient ρ_{kj} characterizes the correlation between the degrees of connected nodes, and, as such, it ranges from -1 to 1. If it is positive, the network is said to show an assortative behavior (sometimes also called "homophily"), since it means that the nodes tend to be connected to other of a similar degree. If it is negative, the network is said to be "disassortative", implying that low-degree nodes tend to attach to the high-degree nodes of the graph, and vice versa. The closer the coefficient is to 1 (or -1), the more intense is the assortative (or disassortative) behavior of the nodes. Just to mention a couple of examples, it has been found that social networks often display an assortative behavior (i.e., high-degree nodes prefer to connect with others of similar degree), while technological and biological networks tend to be disassortative (Newman, 2002, p. 4). Financial networks are prominently disassortative (as it can be verified from the evidence summarized in the Appendix), which means that financial institutions with few connections are more prone to establish links with banks of high degree, and vice versa.

This fact has significant implications, both in terms of the network's structural characteristics and in terms of its stability and systemic risk. For instance, disassortative networks are particularly vulnerable to targeted attacks on their highest-degree vertices, while assortative networks proved to be more resilient to them (Newman, 2002).

The clustering coefficient of the monthly networks is also examined in this paper. It is a measure of the probability that two nodes which are neighbors of a same node also share a link themselves. The clustering coefficient of node i is defined as follows:

$$c_i = \frac{1}{k_i(k_i-1)/2}\sum_{j,h} a_{ij}a_{ih}a_{jh}$$

Basically, it indicates whether two vertices, which are connected to a third vertex, have a connection between them; that is, it states if they form a triangle. The average clustering coefficient quantifies the density of triangles in the graph and is computed as the arithmetic mean of all the individual c_i. It is a measure of the density of interconnections within the network. A high clustering coefficient reveals the existence of stable and lasting relationships among the nodes, with all the potential consequences that it entails, which can be either positive (e.g., an enhanced resilience to random and relatively mild shocks) or negative (e.g., higher level of contagion when facing targeted and intense attacks).

5.3. Centrality and concentration

Centrality is a widely used concept in the context of social networks and it has been extensively studied for decades. It has several interpretations and implications, like the measurement of power, influence or control exerted by a node over the rest of the network. Moreover, centrality measures offer the possibility of ranking nodes according to their "relevance" in a graph. Thus, these indicators are key to detect *too-interconnected-to-fail* vertices, and consequently to estimate the potential vulnerability of a network, as the removal of those nodes could possibly result in a fast fragmentation of the graph (Martínez-Jaramillo *et al.*, 2012).

Several centrality measures have been developed to quantify the relevance of each node in a graph, based on different approaches. All the measures presented here are defined in such a way that a higher value is always interpreted as a larger centrality of a node in the network. This notion is closely related to the determination of the systemic importance (BIS, 2011) of a bank in the financial system, from the perspective of its interconnectedness.

In the context of interbank markets, quoting Martínez-Jaramillo *et al.* (2012), a financial institution can be characterized as "central" if it displays one or some of the following features:

- Possesses numerous linkages with other members of the network (degree).
- The total amount of its assets, liabilities and/or flows in the network are large (strength).
- Its failure could spread contagion in a few steps (closeness).
- Interacts with counterparts which are also relevant (eigenvector).
- Many paths pass through it (betweenness).

Degree Centrality (k_i) is one of the most basic measures of network centrality. According to it, a node is more relevant in a network if it is connected to many other nodes, given that its failure could impact on them directly. For more specific purposes, it is also possible to calculate the out-degree centrality (k_i^{out}) and the in-degree centrality (k_i^{in}) of the nodes.

A similar procedure is applied to compute the strength centrality of each subgroup, taking into account the total strength (s_i) as well as the in-strength (s_i^{in}) and out-strength (s_i^{out}). A high Degree Centrality exhibited by a node does not necessarily mean that the institution has a strong impact on the others, as it could be the case that those various connections actually involve low amounts of money. In contrast, Strength Centrality is useful to assess the relevance of each node or subgroup with respect to the total amounts of liquid funds traded in the market.

The Closeness Centrality (CC) of a node is based on how many intermediaries are required to pass through in order to reach it. This measure is associated with the capability of a node to spread contagion to the rest of the network. It is calculated as the inverse of the average length of the shortest paths from a node i to all the other vertices in the graph. We use a normalized version of this metric, which allows us to compare its values homogeneously among graphs that do not have the same N:

$$CC(i) = \frac{N-1}{\sum_j d_{ij}}$$

In order to find the average closeness of the network, we simply calculate the arithmetic mean of $CC(i)$ for all $i \in N$.

Betweenness Centrality is associated with the strategic location of a node on the network's communications paths. In the case of the call market, this type of centrality reflects the influence of a node on the liquidity channels within the system. Betweenness Centrality reveals how fast potential shocks can spread through the network, while other measures, like the degree or closeness centrality, account for the probability of amplification of shocks to the neighbors of each vertex (Lublóy, 2006). The Betweenness Centrality (B) of a node i is defined as follows:

$$B(i) = \sum_{i \neq j \neq h \in N} \frac{\sigma_{jh}(i)}{\sigma_{jh}}$$

Where σ_{jh} is the total number of shortest paths between j and h, and $\sigma_{jh}(i)$ is the number of shortest paths between j and h that pass through vertex i. Dividing $B(i)$ by (N-1)*(N-2), the measure is normalized, so that it can be treated as a comparable indicator among graphs of different sizes. The average betweenness of the network is derived from the arithmetic mean of the normalized $B(i)$ for all $i \in N$.

The last centrality measure examined in this paper is the Eigenvector Centrality, first proposed by Phillip Bonacich (1972). As its name suggests, the centrality value of node i is given by the ith entry of the eigenvector (***e***) associated to the largest eigenvalue (λ) of the graph's adjacency matrix (A):

$$\lambda \boldsymbol{e} = A\boldsymbol{e}$$

This measure exhibits the peculiarity that it takes into consideration the centrality of the neighbors of a node to compute its centrality. It can be understood as the weighted sum of the direct and indirect connections of the node, at any length. Hence, it takes into account the entire pattern of the network to derive the indicator, with the aim of capturing the inherent complexity of the existing relationships in the graph. This measure exhibits some similarities with the paradigmatic PageRank algorithm, which is used by Google to rank webpages according to the relative importance of their connections, as proposed in the seminal paper of Page *et al.* (1999).

Based on these centrality measures (and adding some control variables that will be detailed below), in Section 7 we estimate the empirical effect of a higher centrality on a bank's capability to negotiate more convenient interest rates in the call market. Other very similar analyses were carried out by Bech and Atalay (2008) for the Federal Funds Market of U.S.A., by Akram and Christophersen (2010) for the interbank market of Norway, by Kraenzlin and von Scarpatetti (2011) for the Swiss market, and by Bräuning and Fecht (2012) for the German case. All these contributions verified the existence of a significant positive effect derived from a greater centrality on the ability to achieve better interest rates in interbank money markets.

This paper applies a similar methodology to the one used by Bech and Atalay (2008). An econometric regression is estimated by Ordinary Least Squares (OLS), including the required control variables to remove potential sources of endogeneity. After that, the robustness of the resulting coefficients is tested by changing alternatively the regressors included in the specification (always computing heteroskedasticity-robust standard errors). All the daily transactions are taken into account individually for these exercises (not their monthly averages). More details on this estimation are provided in Section 7.

Additionally, the centrality analysis is complemented by an assessment of the concentration of liquidity flows in the market. The typical Herfindahl-Hirschman Indices are computed to measure the existing concentration in the lenders' side of the market -HHI(L)-, on the one hand, and among the borrowers -HHI(B)-, on the other.

$$HHI(L) = \sum_i \left(\frac{v_{ij}}{V}\right)^2 \; ; \; HHI(B) = \sum_i \left(\frac{v_{ji}}{V}\right)^2$$

Where v_{ij} and v_{ji} denote, respectively, the total amounts lent and borrowed by each entity i in a specific month (always expressed in real terms)[7], while V refers to the total traded amount of money in the network:

$$V = \sum_i v_{ij} = \sum_i v_{ji}$$

HHI is defined as the sum of the squares of each entity's share of the total amount of money traded in the market. HHI(L) and HHI(B) describe, respectively, the concentration of lending and borrowing by individual nodes in the network. These are indicators often used to measure market power and competition. HHI ranges from 0 to 1. A higher value indicates a greater concentration of liquidity among few participants. As its value decreases, the closer it is to $1/N$, the more competitive the market is, reflecting a more balanced situation regarding the liquidity management within the system. To obtain comparable measures across time, this index is normalized by adjusting it according to the changes in the number of nodes in the market:

$$HHI^* = \frac{(HHI - \frac{1}{N})}{1 - \frac{1}{N}}$$

Consequently, these indicators can be treated in a homogeneous and comparable way across networks of different sizes.

7: It is worth noting that w_{ij} and w_{ji} represent the *average* volume of money traded by each pair of entities i and j during a particular month, while v_{ij} y v_{ji} reflect, instead, the total *sum* of the funds traded by each pair of entities in a month.

5.4. Degree distribution

With the purpose of determining which is the distribution function that best fits to the empirical degree distribution of monthly networks, the methodology proposed by Clauset *et al.* (2009) is applied. This procedure is one of the most widely used in the literature related to these topics (Gillespie, 2015; Martínez-Jaramillo *et al.*, 2012), since it has proven to achieve more robust results than the other existing techniques.

Our main objective is to find out if it is accurate to assume that the degree distributions of the monthly networks behave similarly to that of random graphs (which are best described by a Poisson), or if the empirical data fits better to a "heavy-tailed" distribution, such as, for example, a Power Law or a Lognormal. In the latter case, "unusual" or disruptive events (far away from the mean or median of the distribution) exhibit a relatively higher probability of happening than in the former case. This fact gives rise to very significant consequences in terms of the systemic risk to which the network is subject in each case.

As the Power Law distribution function diverges when the variable in question approaches zero, it is necessary to establish some lower bound (x_{min}) in order to estimate its parameters, based on the empirical data. It is often the case that degree distributions follow a Power Law only in the tail, i.e., for values above the lower bound x_{min}, hence the critical role of an unbiased estimation of its real value.

Table 2 presents the theoretical distribution functions that are fitted to the data in this paper, and the appropriate normalizing constant (C) required to ensure that the sum of probabilities over the domain of the variable totals 1. As it can be easily noted, parameter x_{min} constitutes a prerequisite to estimate the other parameters, which are in turn estimated by the method of Maximum Likelihood (ML). The ML estimators are advantageous because they are consistent and asymptotically efficient[8].

Table 2. **Probability Density Functions tested for the fit to the empirical data**

Name	Distribution: $\boldsymbol{p(x) = Cf(x)}$		Parameters to be estimated
	$f(x)$	C	
Power Law	$x^{-\alpha}$	$(\alpha - 1)x_{min}^{\alpha-1}$	x_{min}; α
Lognormal	$\frac{1}{x} exp\left[-\frac{(\ln x - \mu)^2}{2\sigma^2}\right]$	$\sqrt{\frac{2}{\pi\sigma^2}}\left[erfc\left(\frac{\ln x_{min} - \mu}{\sqrt{2}\sigma}\right)\right]^{-1}$	x_{min}; μ; σ
Poisson	$\frac{\mu^x}{x!}$	$\left[e^{\mu} - \sum_{k=0}^{x_{min}-1} \frac{\mu^k}{k!}\right]^{-1}$	x_{min}; μ; σ

Note: C is the appropriate normalizing constant such that $\int_{x_{min}}^{\infty} p(x)\, dx = 1$ in each case. In turn, $erfc$ is the complementary error function, defined as $erfc(x) = \frac{2}{\sqrt{\pi}}\int_x^{\infty} e^{-t^2} dt$.

The main contribution of Clauset *et al.* (2009) consists in the fact that they choose the value of x_{min} that minimizes the differences between the probability distributions of the empirical data and the best-fit theoretical model (regardless of the specific model selected). A variety of methods are available to measure the distance between two probability distributions, but for non-normal data the most usual is the Kolmogórov-Smirnov or KS statistic,

8: Clauset *et al.* (2009, Appendix B) show a summarized formal proof of this statement.

which is the maximum distance between the Cumulative Distribution Function (CDF) of the data and the CDF of the fitted model:

$$KS = \max_{x \geq x_{min}} |D(x) - P(x)|$$

Where $D(x)$ is the CDF of the data, for values above x_{min}, and $P(x)$ is the CDF of the hypothetical model fitted by ML, for the same region $x \geq x_{min}$. The proposed estimate of x_{min} is then the value of x_{min} that minimizes KS.

It is worth noting that the authors highlighted the fact that this methodology achieves more accurate results provided the sample has a size of about 1,000 or more observations. It constitutes a note of caution that must be taken into consideration while interpreting this type of empirical analyses in the context of financial networks, where the sizes of the data sets are often comparatively modest. In our case, the monthly networks examined are also relatively small, a fact that amplifies potential estimation biases, but very common particularly in networks based on interbank loans.

In order to compute the variance of the parameter estimates (both for x_{min} and for the others) the non-parametric “bootstrap” method is applied.

However, once the parameters of a specific distribution are estimated to fit the data, it is also necessary to analyze whether that distribution represents a plausible description of the data or not. Regardless of the true underlying distribution from which the data set was drawn, it is always possible to fit any distribution. Hence, it is imperative to examine the goodness-of-fit to the real observations. To this purpose, Clauset *et al*. suggest a goodness-of-fit test which generates a p-value that measures the plausibility of the hypothetical model. The test evaluates the “distance” between the distribution of the empirical data and the hypothesized model. This distance is compared with distance measurements for comparable synthetic data sets generated from the same theoretical model, and a p-value is then defined as the fraction of the synthetic distances that are larger than the distance estimated by our original KS. If this p-value is large (close to 1) then the difference between the empirical data and the model can be attributed just to statistical fluctuations, but if it is small, the model would not be a plausible fit to the data.

In practice, after deriving our initial KS statistic, a Monte Carlo procedure is applied, generating 3,000 synthetic data sets from the hypothesized distribution. After that, its parameters are estimated in the same way than before (by obtaining the x_{min} that minimizes the KS statistic and estimating the other parameters by ML), individually for each simulated sample. Consequently, we derive 3,000 KS statistics, one for each synthetic data set. Finally, we compare them with the initial value arising from the first exercise. If the fraction of synthetic KS that are larger than the KS for the empirical data is “big enough”, the evidence would not reject the hypothesized distribution function as a reasonably good fit to the data. The authors choose a p-value ≤ 0.1 as threshold for rejection of the null hypothesis, but they also mention that some researchers could possibly impose the less stringent rule of $p \leq 0.05$.

This paper examines whether the degree distributions of the monthly networks (the total degree distribution as well as the in-degree and out-degree distributions) fit better to a Poisson, to a Power Law, or to a Lognormal distribution (see Table 2). These three theoretical distributions were chosen for several reasons. Poisson distribution describes behaviors similar to those of random graphs, while the Power Law is the paradigmatic case among heavy-tailed distributions. Between these two extreme cases, the Lognormal distribution displays also heavy tails, but exhibits a greater flexibility than a Power Law. This feature usually allows for better fits to empirical data that behave more similarly to fat-tailed distributions but in a less strict way than a Power Law.

After estimating the parameters of each distribution according to a best-fit to the data, the goodness-of-fit test mentioned before is carried out. Then, the performance of the different models is assessed by comparing the log-likelihood levels associated to each distribution, based on the empirical data and the parameter estimates. For instance, if the log-likelihood resulting from the Lognormal fit is higher than the one derived from the other proposed distributions, that would indicate that the Lognormal describes better the data set (in spite of the possible fact that in none of the three cases the hypothesized model is rejected by the goodness-of-fit test).

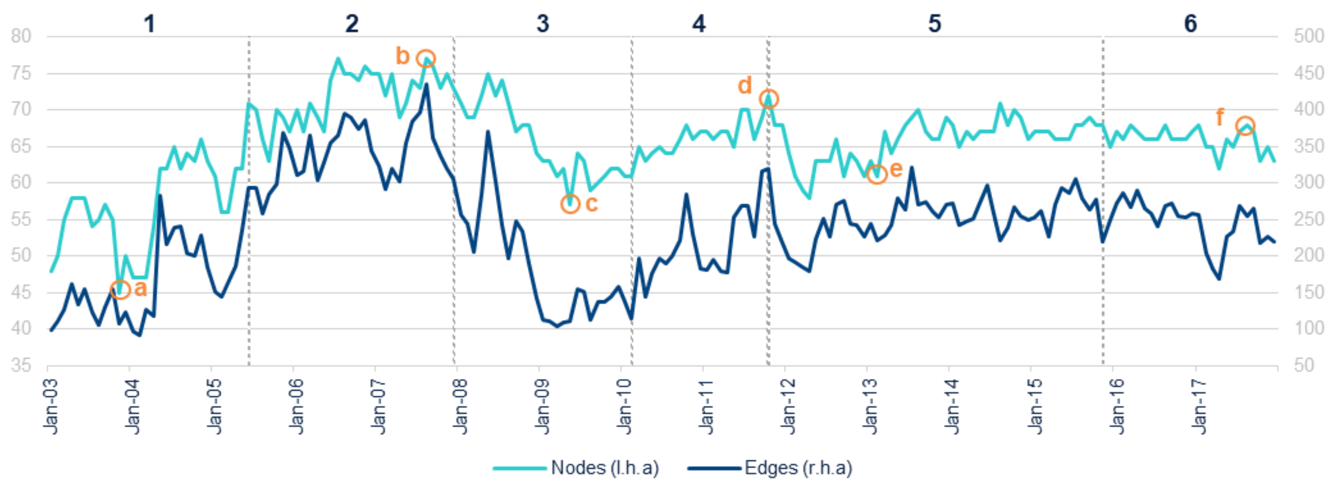
6. Network analysis of the overnight money market

This section is divided into four subsections. Subsection 6.1 reviews some basic topological measures associated with the size of the interbank network and their evolution over time, while 6.2 describes its density and some characteristics concerning its connectivity. Subsection 6.3 explores different centrality measures and studies the concentration of liquidity flows by individual banks. Finally, Subsection 6.4 focuses on the detection of the distribution function that best fits to the empirical degree distribution present in the graphs. The main objective in that subsection consists in elucidating statistically whether that degree distribution can be accurately described by a “heavy-tailed” distribution or not. This feature entails significant insights when carrying out simulations or theoretical stress tests, which are typical exercises implemented by financial regulators over the world.

6.1. Size

One of the salient features of the Argentine interbank network is its relatively small size. Nevertheless, this is a characteristic shared, in general, by overnight loans networks, as they tend to be smaller than graphs based on balance sheet exposures or payments. If we circumscribe to the former group of networks, the Argentine is not the smallest (cf. the Appendix, but it is substantially tinier than, for instance, the Fed Funds network in the U.S.A. (Bech & Atalay, 2008) or the Italian Overnight Money Market (Kobayashi & Takaguchi, 2017).

Figure 4. **Monthly total number of active nodes and edges in the call market**

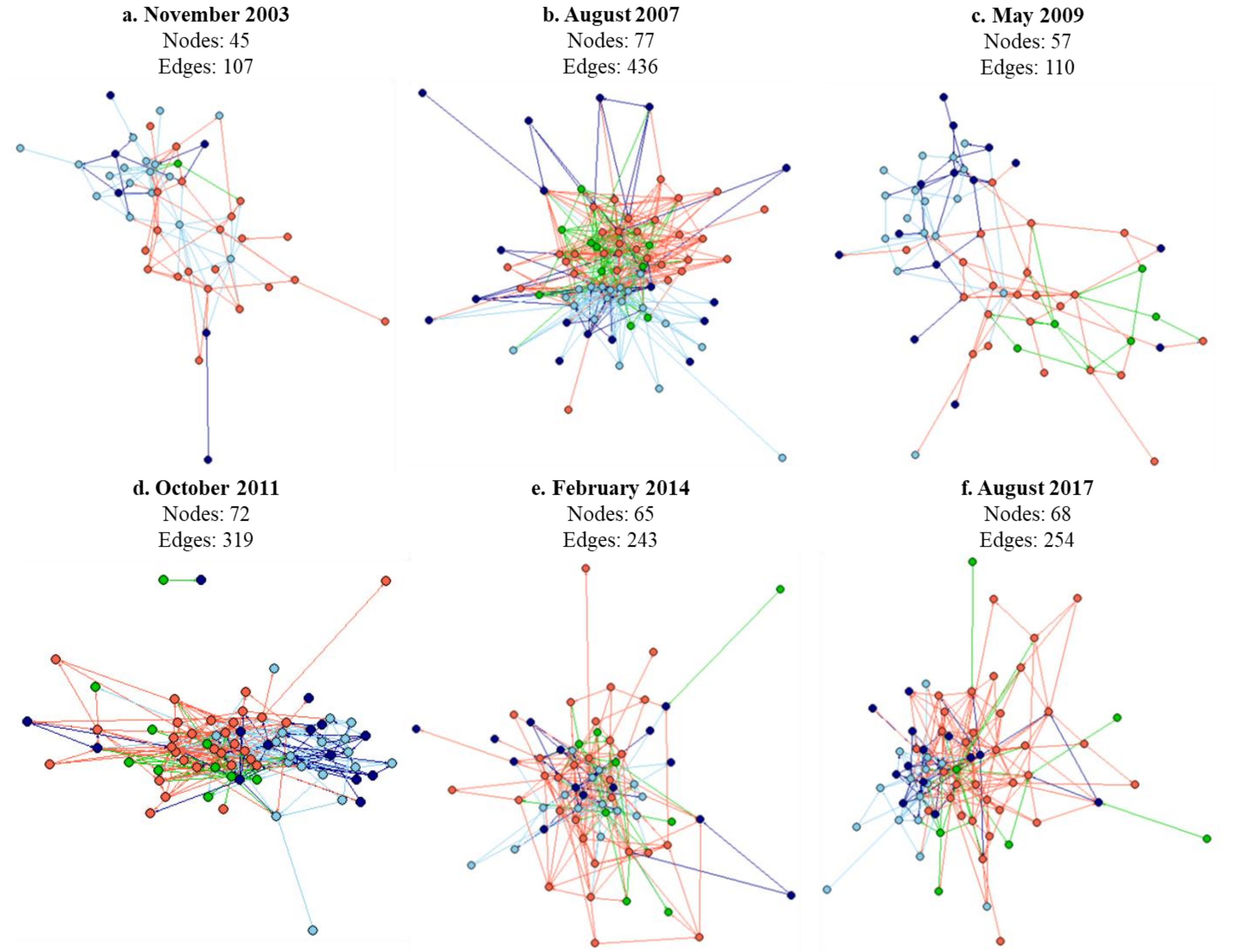


Note: the red circles signal the monthly networks shown in Figure 5. A specific month of each stage was selected in order to display an introductory visual approximation of the network’s structural changes throughout the period under analysis.

Specifically, the number of nodes (i.e., active financial entities in the call market) is not the lowest, compared with other interbank networks, but it is significantly smaller than the largest ones. A similar result emerges for the number of edges, although in this case it is relatively more evident that they are less numerous than in the majority of the other financial networks analyzed so far.

As mentioned in Section 5, the present analysis is focused on the monthly networks. During the period between the years 2003-2017, the monthly average of active nodes was 65.4±5.9 entities, which established an average of 237.5±73.1 edges per month (considering the directed graphs). It is worth highlighting the large fluctuations suffered by these two variables, with their most pronounced movements taking place between 2003 and 2010 (Figure 4). The most intense volatility is observed in the first stage of the period under analysis, mainly associated with the fact that the financial system was still recovering slowly after the 2001 crisis and the sovereign debt default was not solved yet (which hindered the normal conduct of financial operations in the country). 2003 was the year with the lowest average number of active banks (53.6±4.2) and links (127.4±19.8)[9].

Figure 5. **Argentine interbank networks (monthly average)**



Note: Each node represents a financial entity (green: State-Owned Banks; red: Domestic Private Banks; light blue: Subsidiaries of Foreign Banks; dark blue: Non-Bank Financial Institutions). Each edge denotes the existence of at least one loan settled between a pair of entities during the month, and its color is defined by the lender entity. The visualization layout of the nodes was computed by the Fruchterman-Reingold algorithm (1991).

9: In 2009, in the context of the global financial crisis, the number of edges fell to a slightly higher value (128.1±18.9), but the decline was not that significant in the case of the participating nodes (61.4±1.8).

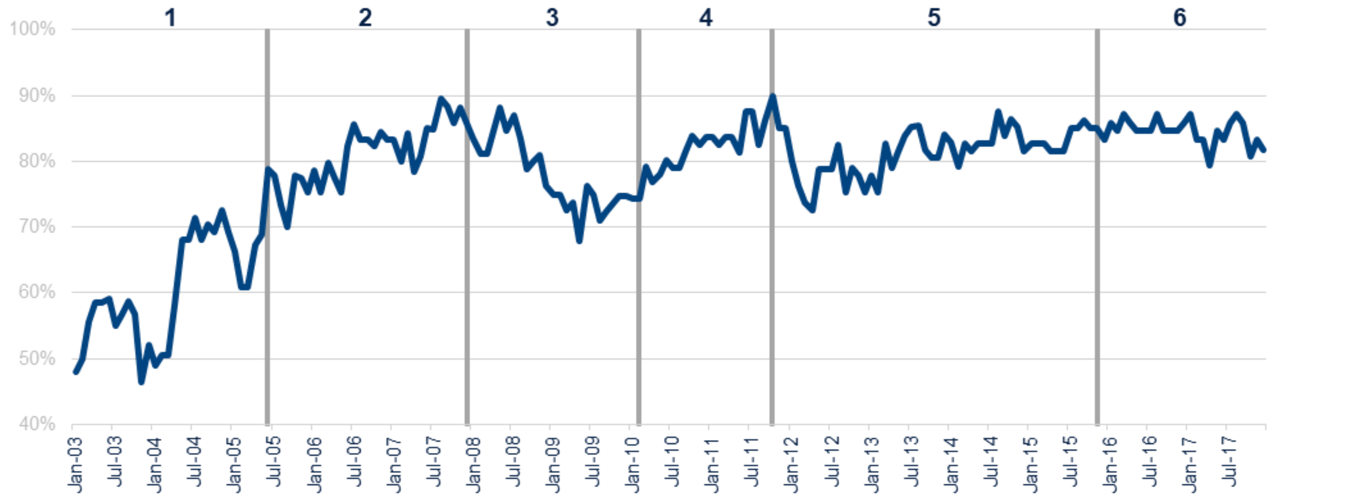
As Argentina recovered from the crisis, the interbank network in 2004 started to grow considerably, both in terms of its edges and its active nodes (Table 3). The percentage of participating banks in the call market with respect to the total number of authorized entities in the system increased from 55% in 2003 to an average of 84.5% in 2007, and then stabilized at around 81.5% during the rest of the period[10] (Figure 6).

Table 3. **Nodes and edges: monthly summary statistics**

Stage*	Date	Nodes					Edges				
		Average	Standard Dev.	Coeff. of variation	Min.	Max.	Average	Standard Dev.	Coeff. of variation	Min.	Max.
1	Jan-03 - Dec-03	54	4.2	7.7%	45	58	127	19.8	15.5%	99	162
1'	Jan-04 - Jun-05	59	6.7	11.3%	47	71	189	58.0	30.7%	92	293
2	Jul-05 - Dec-07	72	3.6	5.0%	63	77	341	40.3	11.8%	259	436
3	Jan-09 - Feb-10	61	1.8	2.9%	57	64	128	18.9	14.8%	103	158
4	Mar-10 - Oct-11	67	2.3	3.4%	63	72	220	48.2	21.9%	144	319
5	Nov-11 - Nov-15	66	2.9	4.4%	58	71	251	29.7	11.8%	180	322
6	Dec-15 - Dec-17	66	1.5	2.3%	62	68	246	29.7	12.1%	168	289

* Stage 1 is subdivided in two parts in this Table, with the aim of showing in more detail the values observed during 2003, year in which the minimums for the whole period took place. 2008 is omitted because the network experienced a continuous shrinkage all year long, so its average values are not illustrative of what really occurred in terms of the network's empirical dynamics.

Figure 6. **Active nodes in the call market** (% of total entities in the financial system)



Source: BBVA Research

During the second stage of the period under analysis the call market displayed the greatest dynamism, reaching peaks in terms of active nodes and links in 2007. Table 4 shows the average number of participating entities, by

10: Only temporary deviations from that average took place in two specific moments: the 2008-09 global crisis and when strict capital controls were established in 2011. During the toughest months of the crisis, the participation ratio hit a minimum of 67.9% (May 2009). The other local minimum is observed few months after the implementation of capital controls, when the participation ratio reached 72.5% in April 2012.

type, in each time interval. It is worth pointing out that SFBs are the only type of entities with a monotonic decrease in number, while the other entities showed an evolution more aligned with the behavior of the network as a whole. This phenomenon suggests that this sort of banks behave in a particular way, less synchronized with the rest of the system.

Table 4. **Average number of participants in the call market, by type of entity**

Stage	Date	Type of entity				Total (average)
		SOB	DPB	SFB	NBFI	
1	Jan-03 - Dec-03	3	21	20	9	54
1'	Jan-04 - Jun-05	4	27	19	9	59
2	Jul-05 - Dec-07	8	31	19	13	72
3	Jan-09 - Feb-10	6	25	18	14	61
4	Mar-10 - Oct-11	6	28	18	14	67
5	Nov-11 - Nov-15	7	29	16	14	66
6	Dec-15 - Dec-17	6	32	15	13	66

Source: BBVA Research

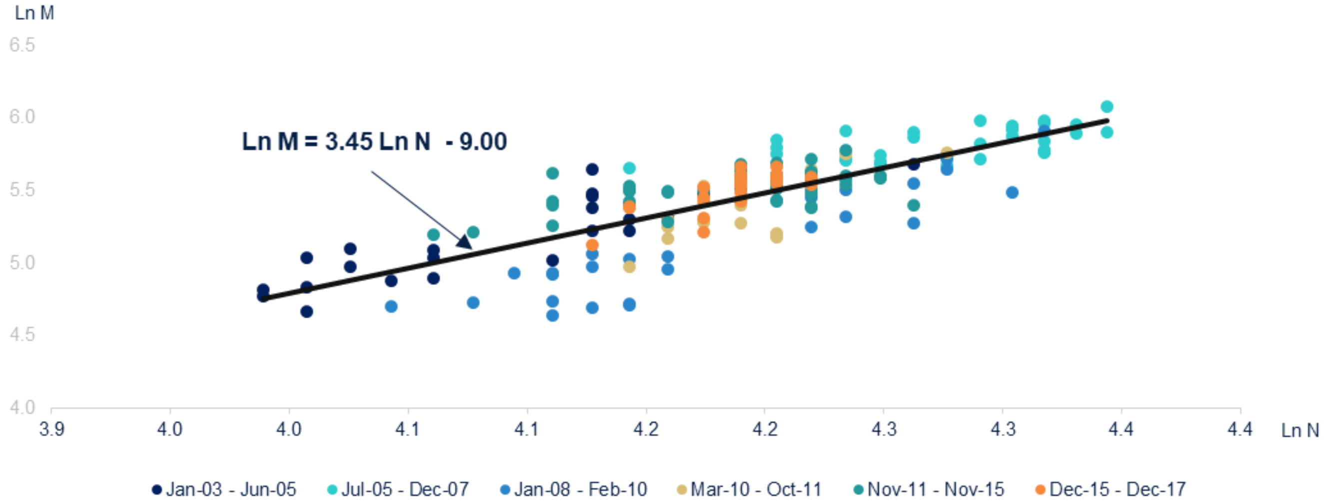
Throughout 2008, when the global financial crisis broke out, a notable contraction of the networks' size materialized. A minimum of 57 nodes and 110 edges was reached in May 2009. The networks remained shrunk around those values until the beginnings of 2010, when they started to increase in size until they got to the levels at which they would then stay relatively unchanged until 2017, around a monthly average of 66 nodes and 243 edges. After the recovery from the crisis, the network showed substantial stability (perhaps in line with the economic stagnation that the country has experienced since 2011), only paused by a transitory decline during the early 2012, in a recessive economic context, after the introduction of severe FX controls that hindered the normal activity of the financial system.

The number of nodes (N) and edges (M) tend to move together. In fact, from a log-log regression between those two variables, it is inferred that $M \alpha N^{3.45}$. This suggests that the average degree of the network -$\langle k \rangle$- increases with order $N^{2.45}$, or, which is the same: $\langle k \rangle \alpha N^{2.45}$ (Figure 7)[11]. This result contrasts with the theoretical papers that assume that the average degree of the network remains fixed over time (that is, they presume implicitly that N and M grow simultaneously in a linear way)[12].

This log-log relationship was present in almost every time stage, with the peculiarity that during the 2008 crisis the intercept seems to lie in a value lower than the average. Only 7 out of the 180 monthly networks analyzed were considered as outliers and excluded from the regression, all of them belonging to the first stage (January and February 2003, and the five months between November 2003 and March 2004). It can be appreciated that those individual networks took place in the most volatile context during the time span under study. After this unstable lapse, the identified relationship between N and M seems to stabilize around the aforementioned levels.

11: This M-N elasticity is significantly higher than the elasticity estimated by Kobayashi and Takaguchi (2017) for the Italian Overnight Market, where they found that $M \alpha N^{1.5}$.
12: See Dorogovtsev and Mendes (2003) for further discussion on this topic.

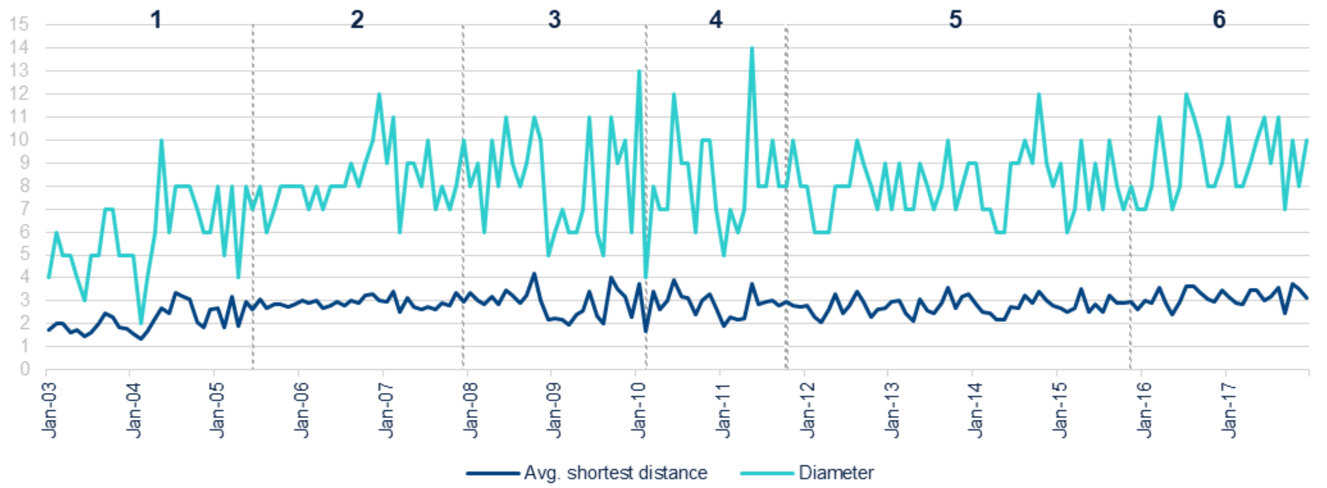
Figure 7. **Log-Log relationship between N and M**



Note: the horizontal axis of the scatter plot depicts the natural logarithm of the number of nodes in each monthly network, while the vertical axis shows the natural logarithm of the number of edges.

Other relevant indicators to measure the size of the networks are the diameter and the average shortest distance. The latter (considering the directed graphs) displayed an average of 2.8±0.5, while the diameter oscillated around 7.9±1.9. These two topological metrics followed similar trajectories, and roughly co-moved with the number of active nodes and edges (Figure 8).

Figure 8. **Average distance and diameter of monthly networks**



Note: the horizontal axis of the scatter plot depicts the natural logarithm of the number of nodes in each monthly network, while the vertical axis shows the natural logarithm of the number of edges.

The average shortest distance of the networks generally remained very stable, showing values between 2 and 3, with few exceptions (which, in any case, also stayed close to that range). During the first stage of the period, the average distance increased from a level lower than 2 to approximately 3, and then remained stable around that number from 2005 until 2008 crisis, when it temporarily fell again to nearly 2. In the years of FX controls it practically did not experience considerable changes (although its volatility was higher than in the second stage), exhibiting a mean of 2.8. In 2016-17 the distances appear to regain an incipient upward path, reaching and surpassing steadily the threshold of 3.

These distances are clearly within the typical range of values displayed by the financial networks of the world (see the Appendix). They are comparatively quite short, which tends to support the hypothesis that also the Argentine interbank network exhibits the characteristics of a “small-world network”.

The diameter followed a similar path, although it was substantially more volatile. It grew from 4 (or less) in 2003 to an average of 8 in the second half of 2004, keeping roughly this mean level thereafter, until 2015. In Stage 6 of the period under consideration, it is also perceived a renewed rise in this indicator (though not abrupt), when monthly networks started to frequently display diameters noticeably above 9.

In conclusion, the size of interbank networks in the call market experienced a significant volatility, specially between 2003 and 2010, when they first increased sharply until 2007, but then shrunk partially because of the global crisis, among other factors. Finally, after a quick recovery from this event, the topological measures studied in this Section stabilized around values substantially higher than the initial ones. Since 2010, all these indicators referred to the size of the networks tended towards stabilization. It is worth mentioning that in 2016-17 the number of edges showed an incipient decay, while the diameter and the distance increased marginally. Nevertheless, these movements are too mild to draw definite conclusions about possible changes in the trends of these structural metrics.

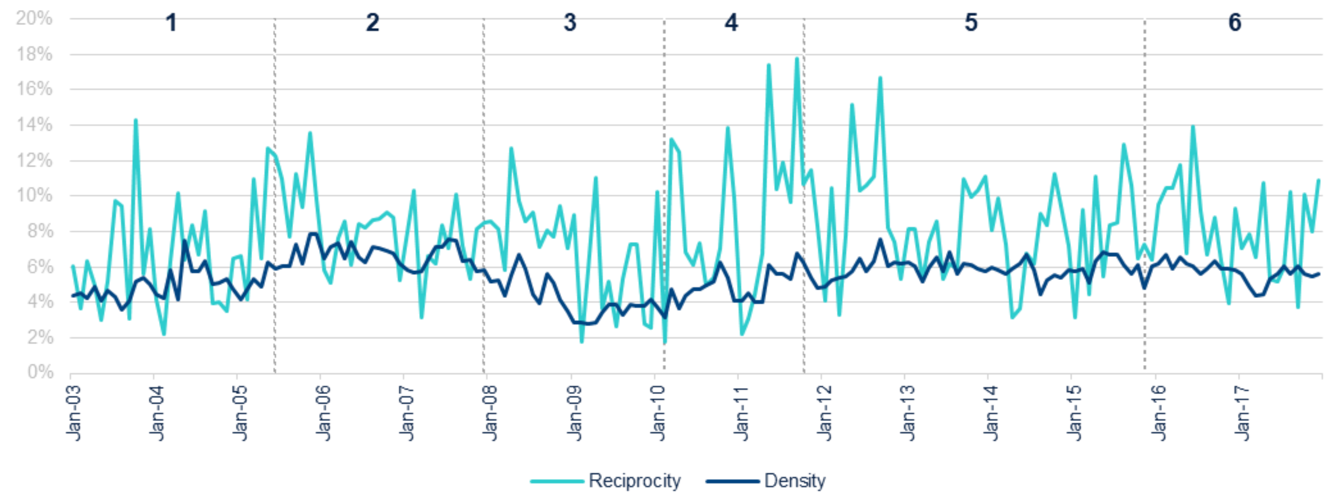
6.2. Connectivity

Interbank networks of overnight loans usually exhibit low density (Hüser, 2015) in comparison with other types of networks studied in various sciences (e.g., biology, physics, social networks, among others). The Argentine financial network here analyzed is not the exception, since only 5.5%±1.1% of the potential number edges actually exists (given the number of active nodes in each month). Thus, monthly networks are far from being “complete” (Figure 9).

The density of the monthly networks followed a similar path to the other topological measures already described: from a starting point of 5% in average during the first stage, it went up to 6.7% in the second (it reached peaks of 7.9%), but, during the crisis, it declined to a minimum of 3.5%. After a recovery of the density levels throughout the fourth stage, in 2011 it reached nearly 6%, at around which it would then stabilize until the end of 2017.

The reciprocity coefficient experienced much more volatility, hitting strikingly high values in 2011. In general, it also shares an evolution comparable with the other metrics mentioned, but its variability makes it difficult to identify patterns as clearly as in the other cases. The average reciprocity of the network was 7.9%±3%, reaching a maximum of 17.7% in September 2011 and a minimum of 1.8% in the beginnings of 2010. These figures are in line with other real-world interbank networks, where the reciprocity is typically higher than the density. However, the average reciprocity level found for the Argentine call market is among the lowest ones.

Figure 9. **Density and reciprocity of monthly networks**



Source: BBVA Research

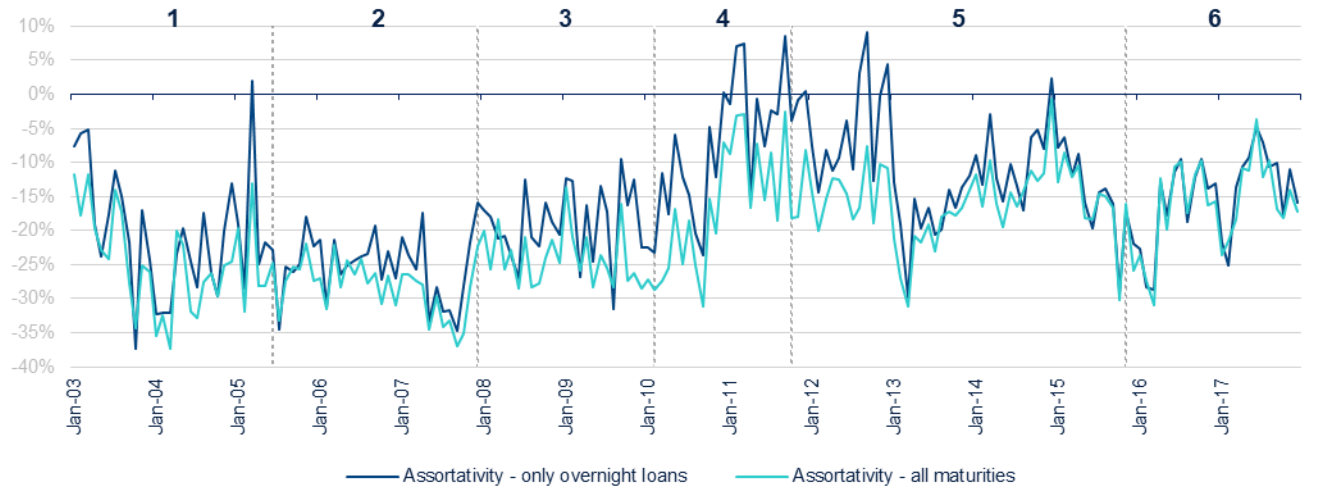
The reciprocity exceeded the level of density in 77.2% of the months. This implies that the network tends to show a higher reciprocity than a random network of equal degree of completeness. That is, the banks are prone to establish two-way relationships between each other with motivations different from a mere randomness. This fact highlights the importance of taking into account the existence of steady (non-random) relationships between the nodes within the call market (at least when evaluating its systemic stability).

Nevertheless, the evidence in this matter is not completely conclusive. Even though the reciprocity coefficient adjusted for the network's density turns out to be 2.5%±3.1% (that is, in average above zero), the fact that, within only one standard deviation away from the mean, the indicator shows negative values weakens to some extent these conclusions. However, in none of the different time stages the adjusted reciprocity coefficient displayed a general average below zero.

The assortativity coefficient was -16.3%±9.4%. This implies that the network is disassortative, which means that low-degree banks are more likely to interact with high-degree banks than with other low-degree ones (i.e., the network is not homophilic). It is the typical behavior found in all the other financial networks analyzed over the world.

This disassortative behavior (that is, a negative assortativity coefficient) was present in 94% of the months (Figure 10). The interbank network displayed a positive coefficient only in 10 out of the 180 months included in the sample. Curiously, that sporadic assortative behavior arose mainly in months during which the reciprocity coefficient reached its highest level, in 2011 and 2012, pointing to the fact that in those moments high-degree entities tended to create edges between each other, in a more reciprocal way than during the rest of the period under analysis. Nonetheless, when not only overnight loans but also all the other maturities are considered, the assortativity coefficient remains negative during the whole period. This fact reinforces the conclusion that the high-degree entities tend to create more links with low-degree entities, but it additionally suggests that the transactions settled with those low-degree banks frequently have maturities longer than a day (while the most connected banks regularly carry out overnight transactions).

Figure 10. **Assortativity coefficient, according to the maturity of the loans considered**



Source: BBVA Research

Over the last seven years of the sample (2011-2017), the assortativity coefficient was in average less negative (that is, nearer to zero in absolute terms) than in the first years. Coincidentally, most of the topological measures of the network were relatively more stable in the last two time-stages. Hence, given the stability of other structural parameters, the network moderated its disassortative behavior (without becoming assortative) in that lapse. In contrast, during the most booming years in terms of the network's growth (2003-07), disassortativity tended to accentuate.

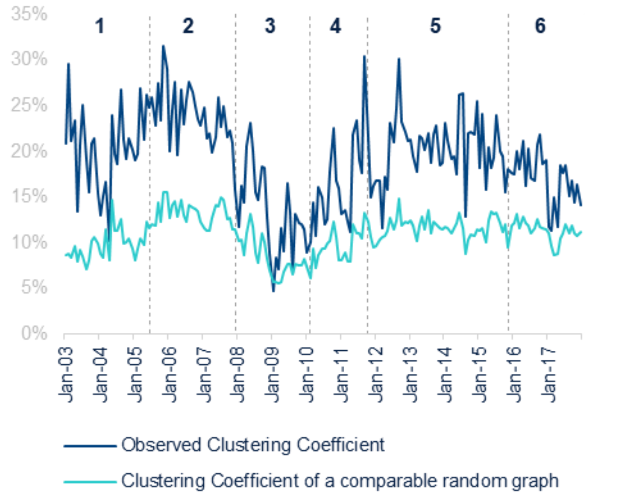
Thus, the identification of the high-degree nodes in the system becomes a central task, since they represent the cornerstone on which the other banks (less connected and with more volatile and smaller trading volumes) can build new links to manage their liquidity during buoyancy periods of the network's activity. In other words, this core of highly interconnected entities represents a kind of "gear" that makes the market work, and where the less connected institutions resort when financial intermediation in general recovers dynamism in the economy.

On another note, the call market shows a level of clustering systematically above that of a comparable random network throughout the period studied, as expected *a priori* (Figure 11). There is only one exception in January 2009, in the context of the global financial crisis. It is usual to find in financial networks the creation of relatively stable clusters, not randomly established, because of the propensity to make lasting relationships among financial agents. This conduct allows them to reduce risks, for instance, derived from moral hazard and adverse selection, inherent to financial markets.

However, although financial networks tend to show clustering coefficients higher than those of random graphs because of the reasons stated above, at the same time the need of risk diversification puts an upper limit to the increase in that indicator. This trade-off explains why clustering tends to be higher in interbank networks than in random graphs but it simultaneously does not reach comparatively high values in relation with other types of real-world networks (e.g., biological or linguistic networks usually show significantly higher coefficients). These clustering levels are similar to those that emerge in empirical scale-free networks.

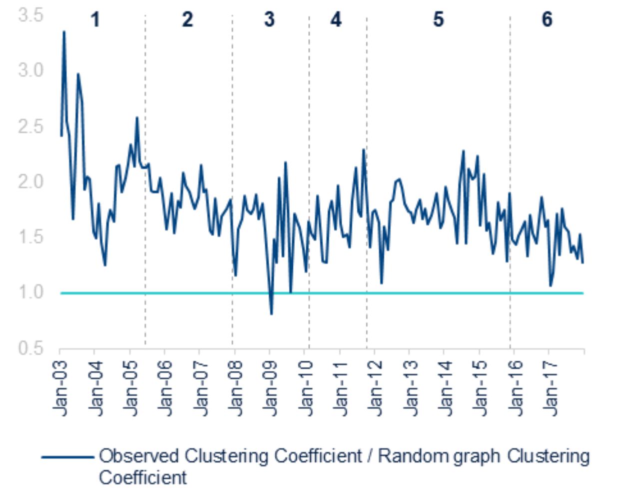
In broad terms, the case of Argentina follows these guidelines, displaying an average clustering coefficient of 19%±5.1%. The evolution of the indicator presents some noteworthy features. During the global financial crisis, the clustering levels of the network decreased towards values similar to those of a random network, while the number of edges and active nodes fell alongside. That means that in a context of systemic financial distress and of decline in the size and connectivity of the network, it showed some symptoms of "randomization". This could be interpreted as a sort of defense mechanism of the network, which could turn it more resilient, avoiding the risks of contagion that usually arise when financial entities are very interconnected.

Figure 11.a. **Clustering coefficient**



Note: The average clustering coefficient observed in the empirical networks is compared with the clustering coefficient that would emerge from a random graph with the same number of nodes (N) and with the same average degree $\langle k \rangle$. The average clustering coefficient of a random network is equal to: $\langle k \rangle / N$.

Figure 11.b. **Relative clustering coefficient**



Source: BBVA Research

After the crisis and the stabilization of the network structure, it maintained relatively higher and invariant clustering coefficients, around 20%, far from the values that would be seen in a comparable random network, until end-2017, when it seems to start showing a new incipient and gradual decline.

Table 5. **Network's topological measures** (average of each period)

Stage	Date	Avg. Distance	Diameter	Density	Reciprocity	Assortativity	Clustering
1	Jan-03 - Dec-03	1.9	5.1	4.5%	6.6%	-17.1%	20.5%
1'	Jan-04 - Jun-05	2.4	6.4	5.3%	6.9%	-23.0%	20.2%
2	Jul-05 - Dec-07	2.9	8.3	6.7%	8.1%	-25.3%	23.9%
3	Jan-09 - Feb-10	2.7	7.6	3.5%	5.4%	-18.7%	10.3%
4	Mar-10 - Oct-11	2.9	8.3	5.0%	9.1%	-6.7%	16.9%
5	Nov-11 - Nov-15	2.8	8.1	5.9%	8.3%	-11.1%	20.2%
6	Dec-15 - Dec-17	3.2	9.1	5.7%	8.2%	-15.1%	17.0%

Source: BBVA Research

In summary, starting from very low levels in 2003, the number of active nodes and edges, the diameter, average distance, density and reciprocity of the network grew altogether in simultaneous with the economy until 2007. During this expansion, disassortativity accentuated, as also did the clustering coefficient. The global crisis produced a significant contraction in all these metrics, and banks' behavior tended towards that of a random network, in terms of its reciprocity and clustering. In 2010-11 almost all the topological measures experienced a notorious recovery, with the peculiarity that reciprocity reached historical peaks along with positive assortativity coefficients among entities. This phenomenon differentiates that recovery phase from the growth observed during the first years of the sample. In 2011, all the indicators got to levels that would remain rather stable in average until 2015. Not many significant changes were witnessed in the years 2016-17, except for an incipient decrease of the relative clustering coefficient (compared with a random graph) and the density of the network, neither of them intense enough to draw categorical conclusions.

6.3. Centrality and concentration

The simplest centrality measure is the average degree of active nodes. Taking into consideration the whole period, financial entities exhibited an average total degree of 7.1±1.8, experiencing movements quite proportional to the number of edges in the network (Table 6). This indicator was clearly heterogeneous among the different types of entities. SFBs were the group with the largest average total degree in the network since 2003 until the global crisis, moment when DPBs acquired this central role until 2017. On the other end, NBFIs represented the group of entities with the lowest average degree during all the period under analysis.

Table 6. **Average total degree, in-degree and out-degree, by type of entity**

Stage	Date	Average total degree					Average in-degree				Average out-degree			
		Total	SOB	DPB	SFB	NBFI	SOB	DPB	SFB	NBFI	SOB	DPB	SFB	NBFI
1	Jan-03 - Dec-03	4.7	2.6	5.0	6.0	2.2	0.6	2.2	3.8	0.3	1.9	2.8	2.3	1.9
1'	Jan-04 - Jun-05	6.2	5.0	6.0	8.7	2.2	0.2	2.6	5.7	0.7	4.8	3.5	3.0	1.5
2	Jul-05 - Dec-07	9.5	10.0	9.8	12.8	3.7	1.7	4.7	8.3	1.4	8.3	5.1	4.4	2.3
3	Jan-09 - Feb-10	4.2	3.7	4.5	5.0	2.8	1.1	2.4	3.0	0.7	2.6	2.0	2.0	2.1
4	Mar-10 - Oct-11	6.6	5.6	7.8	6.8	4.3	2.0	4.1	4.1	1.2	3.6	3.7	2.8	3.1
5	Nov-11 - Nov-15	7.6	6.0	9.3	8.0	4.7	1.8	4.4	5.4	1.9	4.2	4.9	2.6	2.8
6	Dec-15 - Dec-17	7.5	6.1	8.5	8.0	5.1	1.7	3.7	5.4	2.8	4.4	4.7	2.6	2.3

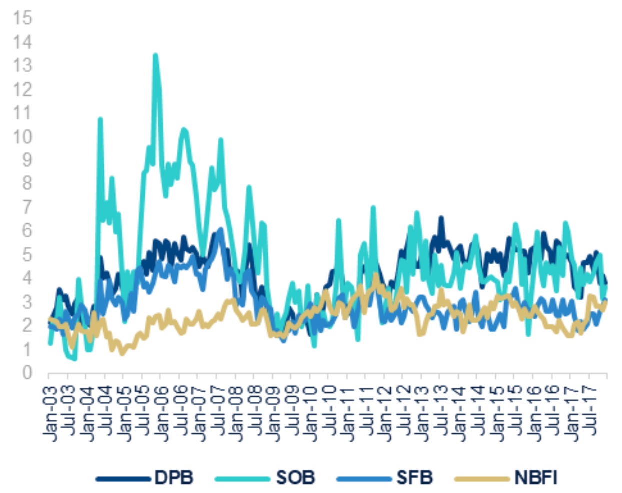
Source: BBVA Research

The different types of entities assumed contrasting roles in the market. SOBs had an average out-degree always higher than their in-degree, becoming the prime liquidity providers of the market. These banks held the highest average out-degree of the network between 2004 and 2008 (Figure 12), the most buoyant years in terms of the call market's activity. The other entities that shared this role of liquidity providers were the DPBs, essentially between 2012 and 2017.

In the opposite side of the market, SFBs erected as the main borrowers of the network, displaying the largest average in-degree during nearly the whole period. NBFIs were the least connected nodes (in the context of this subsection, the least central), playing a more peripheral role in the network's lattice. Most of the time they showed a higher average out-degree than in-degree (that is, those entities were more often lenders than borrowers), except for the last stage, when the opposite occurred. In fact, their average in-degree experienced a growing trend, which explains how NBFIs increased to some extent their centrality in the market over the years.

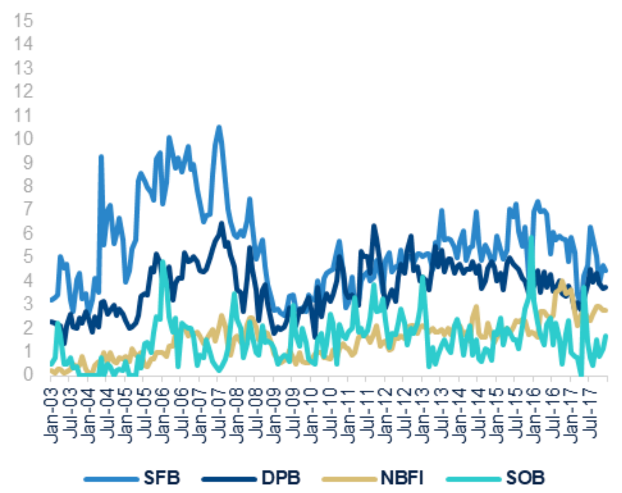
Figure 12 also confirms that DPBs had a crucial role not only from the point of view of liquidity provision to the network but also regarding its absorption. That is, they reached a comparatively high average out-degree as well as in-degree, in relation with the other entities, during the whole period under consideration.

Figure 12.a. **Average out-degree of nodes, by type of entity**



Source: BBVA Research

Figure 12.b. **Average in-degree of nodes, by type of entity**



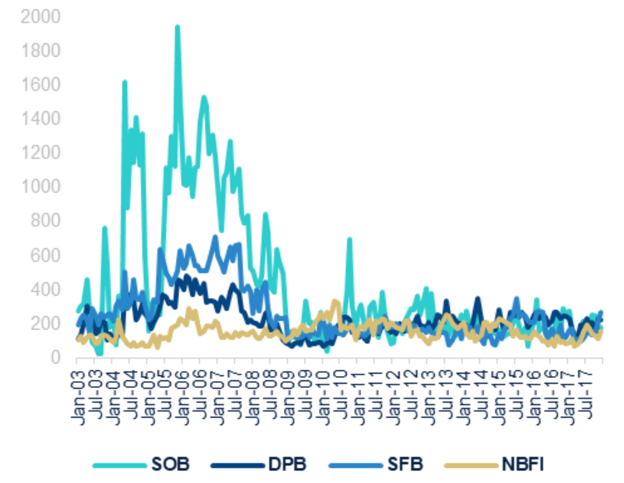
Source: BBVA Research

When the focus is changed to analyze node *strength* (Figure 13), conclusions do not differ significantly, but some key peculiarities deserve to be highlighted. During the most dynamic moments in terms of network's activity, between 2005 and 2007, the main players of the market were fundamentally the SOBs, as lenders, and the SFBs, as borrowers. DPBs also performed a key role in both sides of the market (but with less clear predominance), while NBFIs displayed a substantially higher out-strength than in-strength.

With the outbreak of the global crisis, the average node strength of the system collapsed, from levels of ARS 917±140 million to nearly 260±43 million in 2009. SOBs were the group of banks which experienced the most notorious decline. Since then, no group consolidated as the most central from the out-strength perspective. Despite the fact that since 2010 the nodes in the network have recovered an average total strength of ARS 370±60 million and remained around those levels until 2017, no group emerged visibly as the most central liquidity provider in the market. That role was alternately shared by the different types of banks.

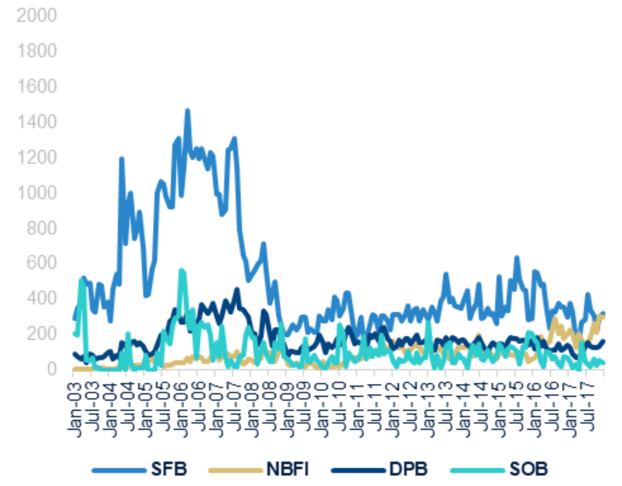
A phenomenon that deserves to be highlighted is the increase of NBFI's out-strength during the recovery from the crisis, as they boosted significantly the market liquidity in 2009 and 2010. This more central role of NBFIs in those years explains at least partially the rise in the network's assortativity (or "homophily") in the fourth stage of the period (Figure 10). During the post-crisis recovery of 2010 and 2011, monthly graphs appeared to be more assortative, as NBFIs abandoned to some extent their usual peripheral role and were more thoroughly interconnected with the core of the network.

Figure 13.a. **Monthly node out-strength, by type of entity** (ARS million, constant prices of 2017)



Source: BBVA Research

Figure 13.b. **Monthly node in-strength, by type of entity** (ARS million, constant prices of 2017)



Source: BBVA Research

Regarding the average in-strength, SFBs were undoubtedly the most central group, as they were the main borrowers in almost every month. Their prominence also experienced a decay during the crisis, but nonetheless they bounced back relatively fast and kept their hegemonic role (from the in-strength perspective) during the rest of the following years. On the other hand, when the average strength of DPBs is considered, the conclusions about their centrality drawn from the analysis of their average degree somehow weaken, but these banks anyway constituted the second main group of borrowers most of the time. It is also remarkable the change in the NBFIs' behavior in 2016-17, when their in-strength centrality grew exponentially, to levels that made them effectively compete with the SFBs for the absorption of the market liquidity. This phenomenon may explain, to some extent, the increase in the network's disassortativity during those two years, as well as the simultaneous reduction in the average clustering coefficient.

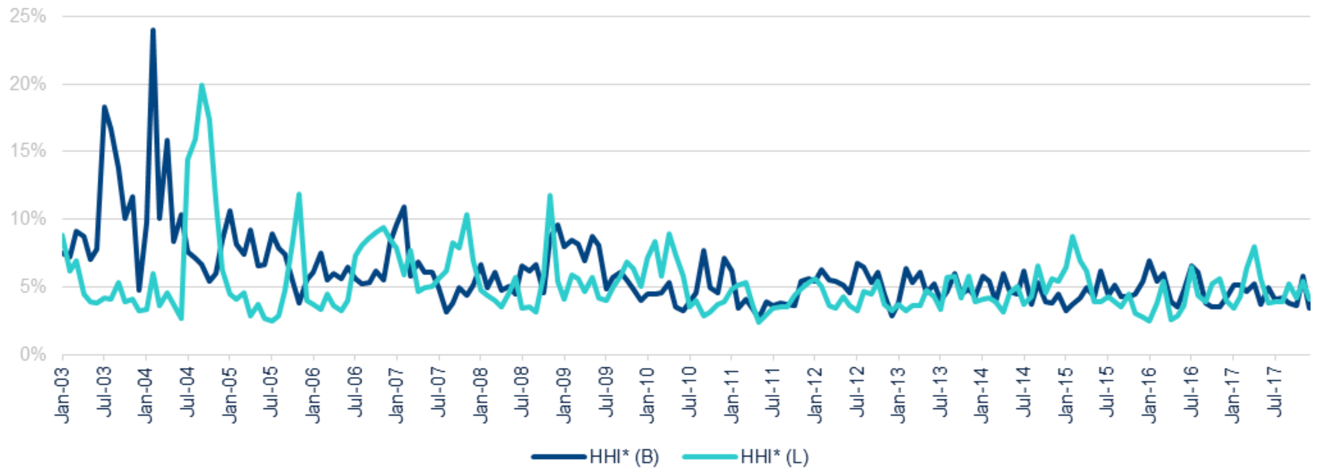
In order to study the concentration of lending and borrowing by individual nodes in the market, Figure 14 presents the evolution of the corresponding Herfindahl-Hirschman Indices (HHI), normalized according to the number of network's participants in each moment[13].

As it can be inferred from the examination of the average node strength, the network was substantially more concentrated between 2003 and 2009 than in the succeeding years, more markedly in the case of borrowers -HHI*(B)- than in the case of lenders -HHI*(L)-. Both HHIs fell (i.e., the market reduced its concentration levels) over the years. Starting with values at an average of around 10% in 2003-04, after the global crisis those indices reached a plateau until 2017, showing average figures of approximately 4.6% for lenders and 4.8% for borrowers.

However, neither of the indices displayed an alarming concentration (in absolute levels) of market's liquidity flows. The network was not significantly concentrated in a few hands, neither on the lenders' nor on the borrowers' side, although the HHI always remained at levels above those that would denote "perfect" competition.

13: When the index is near 100%, it indicates complete concentration of liquidity in one entity's hands, and a value approaching zero represents a perfectly equitable distribution of the market shares among the banks, regarding the allocation or absorption of liquidity in the network.

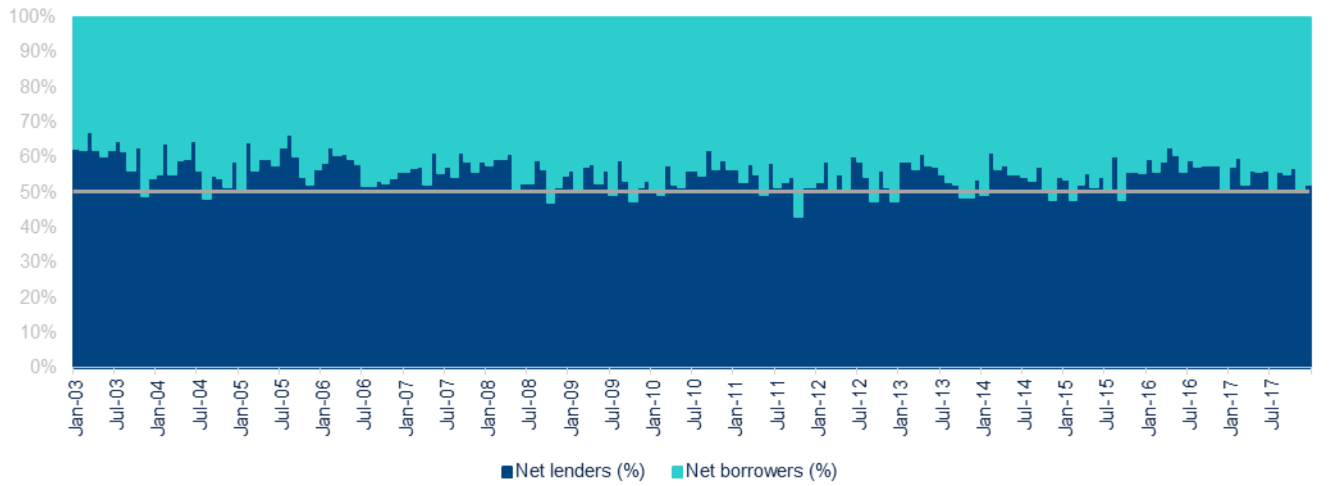
Figure 14. **Herfindahl-Hirschman Index, normalized by the number of entities participating in the market**



Source: BBVA Research

Another approach to study the network's concentration is based on the analysis of the "net liquidity positions" of the entities in the market. They are the result of netting out all the gross flows traded by each entity during a whole month. That procedure allows us to elucidate how many banks were net lenders (i.e., input liquidity into the system) and how many were net borrowers in the network (i.e., captured liquidity from it) during a specific month. In 91% of the months analyzed there was a higher number of net lenders than net borrowers (Figure 15), which reflects that the former were less concentrated than the latter. Notwithstanding, the quantity of net lenders never exceeded the 67.5% of total entities, implying that the network always remained rather equally distributed between liquidity suppliers and demanders.

Figure 15. **Distribution of entities according to their monthly net liquidity positions in the market**
(% of total active nodes in monthly networks)



Source: BBVA Research

The decline in the network's concentration was accompanied by an increasing share of entities that began to act as liquidity "intermediaries", meaning that they not only lent but also borrowed short-term funds in a same month

(Figure 16). In 2003-04, only 32% of the nodes were intermediaries in this sense. That number grew to an average of 51.8% in 2017. In other terms, towards the end of the time period analyzed, nearly half of the institutions participating in the interbank market acted occasionally as both supplier *and* demander of liquid funds during a certain month. This behavior points out the value that the call market entails for Argentine financial entities, as it significantly facilitates their liquidity management.

Figure 16. **Node classification, according to their role in the network**

Source: BBVA Research

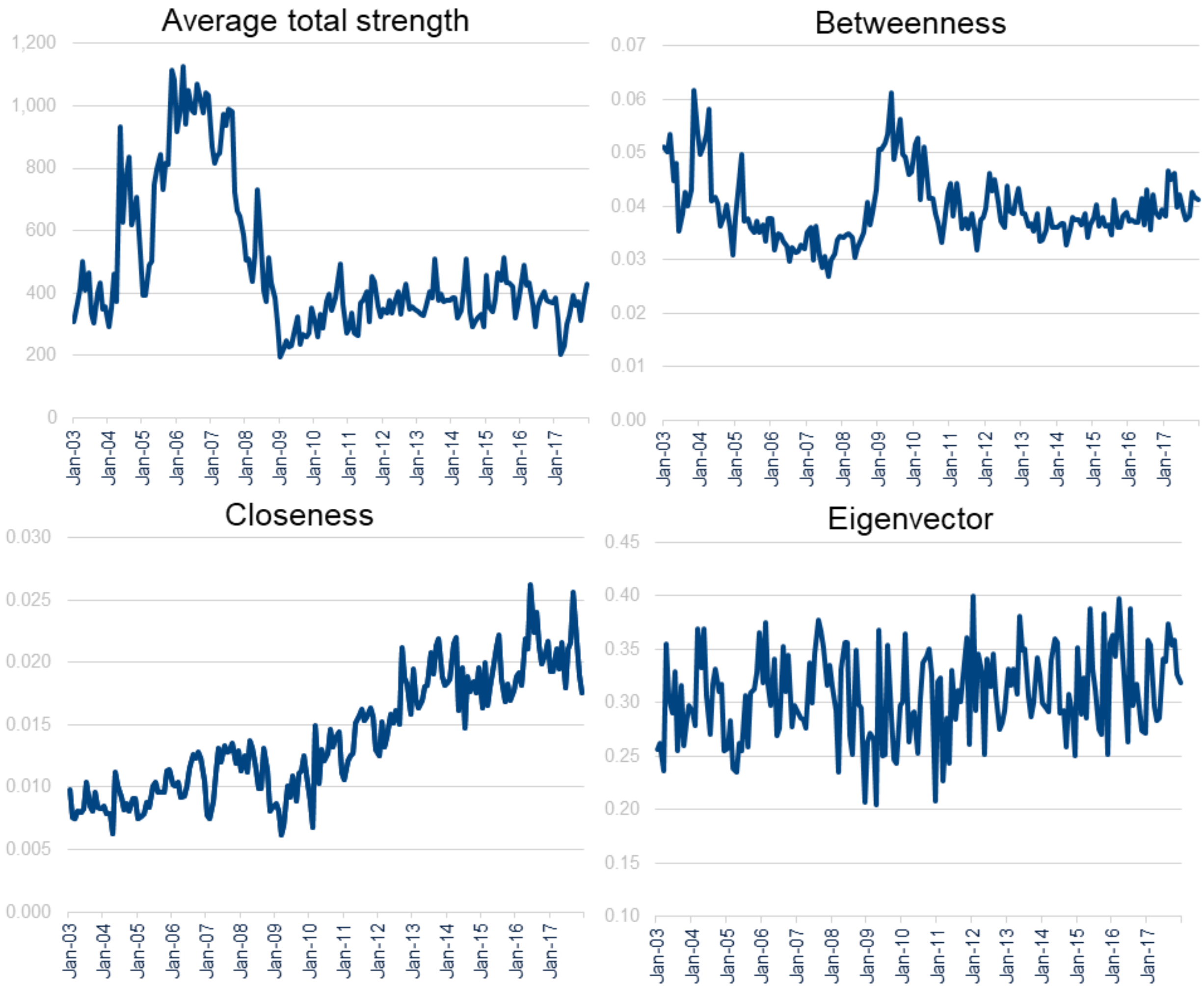
As a complementary approach, with the aim of analyzing the average centralization of the network as a whole, Figure 17 presents three additional metrics based on the concepts of closeness, betweenness and eigenvector centrality. Each centrality measure was computed taking into account the undirected graphs, with the objective of evaluating the average centrality of the nodes in the network in absolute terms, interpreting it as a complex of stable relationships among financial entities.

The different centrality measures provide rather divergent perspectives. One remarkable feature shared by them is that all seem to experience a sort of “break” in their paths after the global financial crisis of 2008. The evolution of the average total strength of the nodes illustrates the magnitude of the change experienced by the network’s structure that year. This indicator registered a strong rise in the years 2005-2007, followed by a collapse with the 2008 crisis, from which it would only partially recover in 2010, when it reached the values that would then remain quite stable until the end of the period.

Betweenness centrality quantifies the average node centrality according to how many shortest paths go through each node, with respect to the existing total number of shortest paths in the network. When the network expanded between 2003 and 2007, this centrality measure decreased substantially, reaching its minimum level during the month in which the network showed the largest size of the whole period (August 2007). With the outbreak of the global crisis, the average betweenness grew sharply, in consonance with the simultaneous contraction of the network. This centrality measure displays a rather opposite behavior to that of the average total strength, since, after that peak in 2009, betweenness shrank again in 2010 and stabilized thereafter, keeping a mild upward trend.

In summary, when the network grew, betweenness centrality reacted by falling, which could be interpreted as a result of the increase in the number of transactions carried out by a higher number of banks. This situation was reversed with the crisis, when the network shrank and got back to the average centrality levels of 2004, although it happened with more entities involved in the market, a fact that highlights even more the preponderance of the effect outlined before. After the subsequent stabilization, the indicator remained fairly stable, in line with the majority of the other topological measures of the graph. Though it is important to notice that the Argentine interbank network does not display high centrality levels compared with other networks, these "mirror" movements with respect to the size and dynamism of the market constitute a useful element to consider when trying to forecast the behavior of the network under different contexts.

Figure 17. **Average total strength of active nodes and centrality measures for monthly networks**



Note: all centrality measures are normalized according to the size of the network in each moment, except for the total average strength, which is computed in constant pesos of 2017. The three centrality measures are calculated in such a way that an increase represents higher average centrality, and vice versa.

Regarding the evolution of the average closeness centrality, a visible break is also detected before and after the crisis. Between 2003 and 2008 it remained at very low and stable levels, but then it started to show a noticeable upward trend, almost tripling its initial values by the year 2017. The latter behavior coexists with the already descripted stability of the other topological features of the network, which seems to imply that entities tend to get "closer" to each other in phases of relative stagnation of the network's structure.

The average eigenvector centrality displayed a much more erratic behavior during the whole period than the other centrality measures, with just a subtle resemblance with the path of closeness centrality. Along the final years of the sample, this type of centrality experienced an incipient increase, which may be explained by the enhanced connectivity of NBFIs in those years (see, for example, Figure 13).

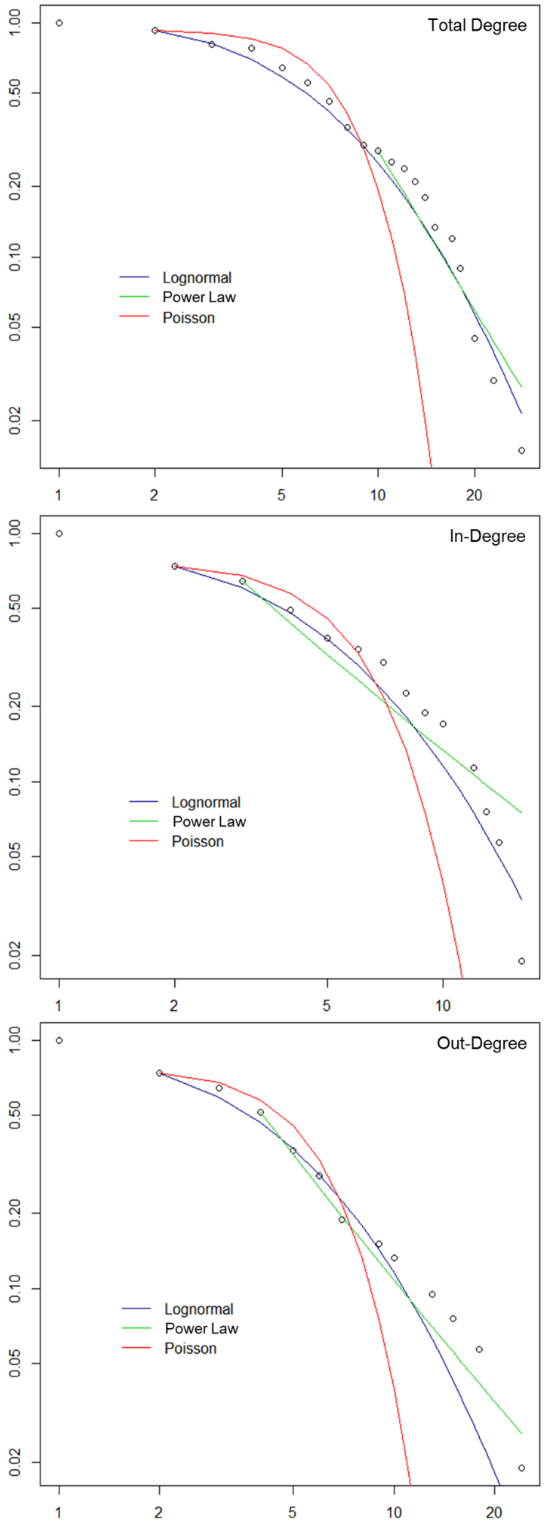
In brief, these three metrics offer different approaches to study the average centrality of the graph. While average betweenness declined with the boom of the network and increased with the crisis, the opposite occurred in the case of closeness (and, although less notably, in the case of eigenvector centrality too). Nonetheless, all of them concur that the average centrality of the network has experienced an, at least slight, upward trend since 2010, a lapse characterized by a relative stability of most of the other topological measures.

6.4. Degree distribution

In the literature on this topic, the usual starting point to analyze the degree distribution of a graph consists in a visual exploration of their Complementary Cumulative Distribution Functions (CCDFs). Figure 18 shows the CCDFs of total degrees, in-degrees and out-degrees of nodes in the average network of December 2016. This particular month was chosen as a representative example because the topological features of its graph are very close to the global average of monthly networks over the whole period.

The degree distribution (of total degrees, as well as of both out- and in-degrees) shows “heavier” tails than a Poisson, which is typically the distribution observed in the context of a random network. Lognormal distribution appears to be the best fit to most of the observations. However, in the case of out-degrees the evidence also provides some support to the hypothesis of a Power Law behavior in the tails of their distribution. In any case, these two latter distributions are both usually said to be “heavy-tailed”, which means that the emergence of extreme events, that is, very far away from the mean, are significantly more likely to occur than in the context of normal or exponential distributions (or Poisson in the discrete case). In the specific case of the interbank network under analysis, this preliminary result indicates that there is a large number of banks with few links, coexisting with a small number of highly interconnected entities, key to the smooth functioning of the network.

Figure 18. **Complementary Cumulative Distribution Functions of nodes' degrees**



Note: Based on the degree distribution of the December 2016 network. This particular network is one of the most similar to the global average of monthly networks over the period (67 nodes, 258 edges). Axis are in log-scale.

After applying the methodology introduced by Clauset *et al.* (2009) to define if the lognormal distribution fits statistically to the monthly empirical networks (and therefore estimated the corresponding total of 180 p-values), it results that in 90% of the cases the null hypothesis of lognormal fit is not rejected for the total degree distribution, considering a type 1 error probability of 10%. Reducing this latter threshold to 5%, the null hypothesis is not rejected in 95% of the months. Those percentages of non-rejection are 88.3% and 92.8%, respectively, for the in-degree distribution, and 91.1% and 95.6% in the case of out-degrees (Table 7). Thus, in almost every month the null hypothesis of lognormal fit is held true, more strongly in the case of the out-degree distribution.

Table 7. **Percentage of monthly networks with a degree distribution that does not reject the lognormal hypothesis**

Stage	Date	Total degree			In-degree			Out-degree		
		p-value > 0.1	p-value > 0.05	Average Xmin	p-value > 0.1	p-value > 0.05	Average Xmin	p-value > 0.1	p-value > 0.05	Average Xmin
1	Jan-03 - Jun-05	90.0%	93.3%	2.9	93.3%	93.3%	2.7	93.3%	100.0%	2.0
2	Jul-05 - Dec-07	90.0%	93.3%	6.3	96.7%	96.7%	2.7	93.3%	93.3%	4.3
3	Jan-08 - Feb-10	92.3%	92.3%	3.1	88.5%	88.5%	2.7	88.5%	88.5%	1.5
4	Mar-10 - Oct-11	90.0%	100.0%	3.6	80.0%	90.0%	3.9	85.0%	90.0%	2.9
5	Nov-11 - Nov-15	89.8%	98.0%	4.5	85.7%	91.8%	4.0	89.8%	95.9%	2.9
6	Dec-15 - Dec-17	88.0%	92.0%	5.0	84.0%	88.0%	3.4	96.0%	100.0%	2.4
Jan-03 - Dec-17		**90.0%**	**95.0%**	**4.4**	**88.3%**	**92.8%**	**3.2**	**91.1%**	**95.6%**	**2.7**

Note: This Table includes all the months of the year 2008 (they were not included in other Tables, given that they belong to a transition lapse between two different network structures, so their inclusion to compute the average topological measures of Stage 3 would dilute the resulting effects derived from the crisis). Here, those months are included with the purpose of examining if the degree distribution of the network changed during each month of the whole period.

The lower bound values of the distribution (x_{min}), needed to estimate the other parameters, turned out to be low, which means that the number of observations removed to perform the estimation is relatively small (compared with the total range of the variable). In fact, the minimum cut-off in the case of total degrees is 4.4 in average (versus an individual maximum number of 36 degrees), 3.2 for the in-degrees (versus a maximum value of 27), and 2.7 for the out-degrees (versus a maximum of 23). It is important to notice again that these are relatively small networks compared with other analyzed by other sciences (e.g., biology, physics, linguistics, social networks, etc., where nodes and edges can easily reach thousands or even millions). Hence, the computations in this paper are clearly subject to potential small-sample biases and other problematic issues related to the lack of abundant observations.

Two fundamental parameters are needed to specify a Lognormal distribution: the mean (which defines the *scale* of the distribution) and the standard deviation (which defines the *shape*). The estimates of the former parameter follow a similar evolution to that of the network's average degree. The mean for the lognormal distribution of total degrees is 1.9±0.51, it is 1.7±0.51 for in-degrees and 1.3±0.71 for out-degrees.

When compared with other empirical distributions that can be fitted by a Lognormal[14], these parameters are in line with those found in the context of social sciences, economics and linguistics. They are also similar to the parameters observed in many studies on medicine or geology, while the standard deviation found here for the Argentine interbank network is significantly lower than those found in many studies about ecological or environmental topics.

14: See Limpert, Stahel, and Abbt (2001) for a survey of studies that found empirical lognormal distributions in the context of several sciences.

Table 8. **Estimation of Lognormal parameters of monthly networks' degree distributions**

Stage	Date	Total degree			In-degree			Out-degree		
		Mean	Std. Dev.	CV	Mean	Std. Dev.	CV	Mean	Std. Dev.	CV
1	Jan-03 - Jun-05	1.6	0.7	43%	1.4	0.8	57%	0.9	0.8	85%
2	Jul-05 - Dec-07	2.3	0.6	26%	1.9	0.8	41%	1.7	0.6	34%
3	Jan-08 - Feb-10	1.7	0.6	35%	1.4	0.6	46%	0.6	0.7	124%
4	Mar-10 - Oct-11	1.8	0.6	33%	1.7	0.6	37%	1.3	0.6	46%
5	Nov-11 - Nov-15	2.1	0.6	28%	1.8	0.7	37%	1.4	0.7	50%
6	Dec-15 - Dec-17	2.0	0.6	28%	1.8	0.6	35%	1.3	0.7	53%
	Jan-03 - Dec-17	**1.9**	**0.6**	**31%**	**1.7**	**0.7**	**42%**	**1.3**	**0.7**	**54%**

Note: The Table shows the average value of the parameters in each stage, based on the monthly estimates.

With the purpose of comparing the Lognormal goodness-of-fit with that of other distributions usually studied in specialized literature, the log-likelihood derived from the Lognormal hypothesis is contrasted with the resulting log-likelihood of a Poisson and a Power Law fitted to the observations (Table 9).

Table 9. **Percentage of monthly networks in which the log-likelihood of the lognormal fit is higher than the log-likelihood derived from fitting other distributions**

	Log-likelihood Lognormal > Power Law	Log-likelihood Lognormal > Poisson
Total degree	98.3%	96.7%
In-degree	99.4%	96.1%
Out-degree	100.0%	97.2%

Source: BBVA Research

Applying the same optimal x_{min} that emerges from a Power-Law fit to compute both log-likelihoods, in 98.3% of the cases the log-likelihood derived from the Lognormal fit to the total degree distributions is higher than the log-likelihood derived from the Power Law fit. This result also arises in 99.4% of months for the in-degree distributions and in 100% of the monthly out-degree distributions. From an analogous procedure, it is concluded that the Lognormal distribution describes the data better than a Poisson in 96.7% of months in the case of total degree distributions, in 96.1% of the in-degree distributions and in 97.2% of out-degree distributions.

In summary, the Lognormal distribution, with the parameters shown in Table 8, is the one that best fits in general to the empirical data of the interbank loans network, with just a few exceptions. After a detailed examination of these exceptions (which represent only a 10% of total cases), no clear regularities emerge that could systematically explain the rejections to the Lognormal hypothesis. The rejection of this hypothesis is not concentrated in any of the time stages of the period. In addition, those exceptional networks do not show any peculiar topological feature.

In conclusion, this heavy-tailed distribution seems to be the most suitable to describe the histogram of total degrees, as well as in- and out-degrees. This phenomenon has critical implications when assessing the probability of disruptive events and financial fragility, so it turns out to be a key input to take into consideration for the design of macroprudential and banking regulation.

7. Effects of node centrality on bilateral interest rates

With the aim of measuring the potential effects derived from node centrality on the bilateral interest rates that banks are able to agree in the call market, a set of regressions were carried out applying OLS (with Heteroskedasticity-Robust standard errors). The dependent variable in this analysis is the interest rate differential between the bilateral rate agreed in each operation and the average rate settled in the market the same day. This differential is defined as a *percentage* of the average market rate. Formally, the main goal is to estimate the impact of node i's centrality (measured by different indicators) on the following variable:

$$r = \frac{call_{ijt} - call_t}{call_t} \quad (6.1)$$

Where:

- $call_{ijt}$: Interest rate agreed between entity i and entity j on day t.
- $call_t$: Average interest rate settled in the market, defined as the volume-weighted average interest rate of all the transactions on day t.

This specific definition of the dependent variable (as a percentage of the market rate, and not in basis points, as it is the case, for example, in Bech & Atalay, 2008) is useful to avoid biases derived from the substantial volatility experienced by the average call rate during the period analyzed (see Figure 1), and allows to focus exclusively on the *relative* spread between the bilateral interest rates settled by financial entities in each one of their particular transactions and the average market rate.

On that basis, nine different regressions were computed using the following generic form:

$$\begin{aligned} r = {} & \alpha + \beta_1 1(centrality\ of\ lender > centrality\ of\ borrower) + \\ & \beta_2 1(assets\ of\ lender > assets\ of\ borrower) + \gamma_1 D_{type\ of\ lender} + \\ & \gamma_2 D_{type\ of\ borrower} + \gamma_3 X + \varepsilon \end{aligned} \quad (6.2)$$

Where:

- β_1 is the coefficient of interest in our analysis, as it quantifies the effect on bilateral interest rates explained by the fact that the lender is more central than the borrower. On the other hand, β_2 measures the impact derived from the fact that the lender has a bigger size than its counterparty (in terms of their assets or their deposits). These effects are estimated thanks to the inclusion of binary variables that, in the case of the variable associated to β_1, take the value 1 when the lender is more central that the borrower, or, in the case of β_2, when the former has a bigger balance sheet than the latter; and take the value 0 when the opposite happens.
- The D_i are vectors of dummies included to take into account the type of entities involved in the transaction. That is, to measure the difference in interest rates when state-owned banks or private entities (domestic or

foreign) or NBFIs are the lenders/borrowers of the loan. γ_1 and γ_2 are the vectors of coefficients associated to this set of control variables.

- X stands for a vector of control variables included to consider specific features of each loan in particular. For instance, the amount of money (in real terms), maturity in *calendar* days (as all the loans considered have a maturity of 1 *working* day), etc.
- α is the constant, and, as such, it contains all the base categories of the dummy variables included in the regression.

Table 10 shows the resulting estimates for nine regressions based on the generic form (6.2), combining different centrality measures and control variables. In the first place it is worth noting that including individually any of the five centrality measures computed here (columns 1-5 of Table 10), in all cases their associated coefficient is positive and statistically significant (with p-values lower than 1%). This implies that a lender that is more central in the network (defining this concept by any of the measures discussed here) than its counterparty tends to settle a higher interest rate than the market average of the day.

The most prominent effect is derived from exhibiting a higher *degree* centrality (column 1 in Table 10), in which case the lender is able to settle, on average, an interest rate 1.32% above the market call rate. A similar effect, though slightly lower, is caused by having a higher centrality measured in terms of average strength: it allows the entities to lend at a rate 1.11% above the market average (column 5). The other three metrics (closeness, betweenness and eigenvector centrality) appear to be less effective, with an impact of nearly half of the effects observed in the first two cases. Anyway, they show a positive impact too, statistically and economically significant (columns 2, 3 and 4).

Before analyzing the outcomes of combining different centrality measures in the same specification, it is worth reviewing first the other coefficients, which tend to remain stable in all the nine columns of Table 10.

Regarding the type of lender entity, DPBs (the base category of the corresponding dummy) are those who provide funds at the highest interest rates, while NBFIs, on average, lend money at the lowest rates of the market. From the perspective of the borrowers, NBFIs tend to obtain the most expensive loans, followed by SOBs in the second place, while SFBs tend to borrow at the most convenient rates. Both the order of the groups of entities as well as the magnitude of the coefficients remain stable in all specifications. It is relevant to control for the type of entity involved in each transaction in order to take into account the effects derived from the type of business that each group runs, which is qualitatively different in each case. All the coefficients computed for these variables are statistically significant (with p-values below 1%) and their sizes reflect the differences in the businesses that each entity conducts in the financial system.

When considering the specific characteristics of each loan, it turns out that none of the controls included have significant effects in economic terms. The maturity in calendar days does not show a statistically significant impact. The amount of the loan does exhibit a statistically significant impact, though economically negligible (less than 0.001% of the market rate). The number of days until the end of the month (when the reserve maintenance period for banks ends) explains in some cases a negative and statistically significant effect (i.e., the farther the end of the month, the lower the rates asked by lenders), but it is also economically negligible. Something similar occurs in the case of the market call rate, which is associated to a negative coefficient (that is, the higher the market rate, the lower the differential between it and the bilateral rates), statistically significant, but it is below 0.2%, which makes it rather irrelevant in economic terms.

Table 10. **Dependent variable: interest rate differential between bilateral rates and the average market rate of the day, as a percentage of the market rate (r)**

	Coefficients								
Variables	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
Centrality Measures									
Lender > Borrower, Degree	0.0132**						0.0167**	0.0171**	
	(0.0007)						(0.0011)	(0.0011)	
Lender > Borrower, Closeness		0.0066**				0.0052**	0.0050**	0.0042**	0.0049**
		(0.0006)				(0.0008)	(0.0008)	(0.0008)	(0.0008)
Lender > Borrower, Betweenness			0.0044**			-0.0007	-0.0029**	-0.0003	0.0001
			(0.0006)			(0.0008)	(0.0008)	(0.0008)	(0.0008)
Lender > Borrower, Eigenvector				0.0069**		0.0052**	-0.0053**	-0.0080**	-0.0011
				(0.0006)		(0.0007)	(0.0010)	(0.0010)	(0.0008)
Lender > Borrower, Strength					0.0111**				0.0107**
					(0.0007)				(0.0008)
Size of financial entity									
Lender > Borrower, Assets	0.0409**	0.0441**	0.0441**	0.0430**	0.0398**	0.0431**	0.0412**		0.0411**
	(0.0008)	(0.0007)	(0.0007)	(0.0008)	(0.0008)	(0.0008)	(0.0008)		(0.0008)
Lender > Borrower, Deposits								0.0445**	
								(0.0007)	
Lender > Borrower, Liquidity	-0.0024**	-0.0027**	-0.0031**	-0.0028**	-0.0028**	-0.0025**	-0.0023**	-0.0004	-0.0033**
	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)	(0.0006)
Type of Lender									
State-Owned Bank	-0.0135**	-0.0129**	-0.0127**	-0.0133**	-0.0138**	-0.0132**	-0.0134**	-0.0150**	-0.0127**
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Subsidiary of Foreign Bank	-0.0279**	-0.0267**	-0.0277**	-0.0273**	-0.0281**	-0.0267**	-0.0274**	-0.0269**	-0.0306**
	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Non-Bank Financial Institution	-0.0388**	-0.0382**	-0.0390**	-0.0389**	-0.0397**	-0.0381**	-0.0383**	-0.0302**	-0.0378**
	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)	(0.0009)
Type of Borrower									
Non-Bank Financial Institution	0.1628**	0.1671**	0.1669**	0.1658**	0.1644**	0.1657**	0.1631**	0.1680**	0.1699**
	(0.0012)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0012)	(0.0011)	(0.0011)
State-Owned Bank	0.0530**	0.0579**	0.0576**	0.0564**	0.0544**	0.0563**	0.0534**	0.0622**	0.0608**
	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)	(0.0017)
Domestic Private Bank	0.0496**	0.0518**	0.0508**	0.0503**	0.0477**	0.0512**	0.0504**	0.0518**	0.0528**
	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0007)	(0.0008)
Loan characteristics									
Call rate, market average	-0.0017**	-0.0016**	-0.0016**	-0.0016**	-0.0017**	-0.0016**	-0.0017**	-0.0005**	-0.0005**
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Maturity	0.000005						0.000008		
	(0.0003)						(0.0003)		
Amount	0.000005*						0.000005*	0.0000	-0.00001**
	(0.0000)						(0.0000)	(0.0000)	(0.0000)
Days until end of the month	0.0000						0.0000	-0.0001*	-0.0001*
	(0.0000)						(0.0000)	(0.0000)	(0.0000)
Time dummies									
Monthly	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Annual	No	No	No	No	No	No	No	Yes	Yes
Constant	-0.0314**	-0.0321**	-0.0300**	-0.0308**	-0.0299**	-0.0328**	-0.0320**	-0.0648**	-0.0525**
Adjusted R²	0.1668	0.1661	0.1659	0.1661	0.1665	0.1663	0.1670	0.1908	0.1875

* Significant with a p-value<0.1. ** Significant with a p-value<0.01. Note: Each column shows a set of coefficients estimated according to a particular specification based on (6.2). Standard deviations are displayed in parenthesis. The R^2 was adjusted according to the number of regressors included.

On average, a lender with more assets that its counterparty is able to settle an interest rate between 4% and 4.4% higher than the market rate for a loan. This coefficient is stable and significant across all specifications, both in statistical and economic terms. If, instead, the size of the entities is measured from the other side of their balance sheets, that means, considering the volume of their deposits, the associated coefficient remains practically unchanged. This result is useful to assess the robustness of the estimation of this particular parameter (regression 8 in Table 10). Overall, these results are in line with those found by similar empirical studies, such as Anastasi *et al.* (2010), Akram and Christophersen (2010) for the interbank market of Norway, and Bräuning and Fecht (2012) for the German case.

Individual liquidity levels also affect bilateral rates. This effect is statistically significant in all the specifications in which the assets are included as a proxy of the size of the entity, and exhibits values between -0.2% and -0.3%. That is, if the lender has higher liquidity levels than the borrower, the settled rate of an operation between them would tend to be 0.2%-0.3% lower than the average market rate. But if this variable is included as a regressor jointly with the deposits (instead of the assets), the collinearity between these two variables turns the coefficient associated to liquidity non-significant to explain r.

Specifications 6, 7, 8 and 9 regress r on different combinations of centrality measures, with the aim of examining their partial effects and potential complementarities. A first important result in this sense is that the coefficient associated to betweenness centrality turns out to be unstable and many times non-significant when included jointly with other centrality measures. Something similar occurs in the case of eigenvector centrality. In contrast, closeness centrality always appears stable and significant, at around 0.5%, regardless of the combination of variables included.

Degree and strength centrality proved to be the most relevant to explain interest rates differentials. In the first case, its associated coefficient even increases when it is included together with other metrics, to a figure near to 1.7%. This value is both statistically and economically significant. Strength centrality remains around 1.1%, also stable and significant even upon changes in the specification.

In conclusion, the evidence seems to support the idea that node centrality proves to be a relevant factor at the time of negotiating a more convenient rate in the call market, even after taking into account the effects derived from the size of the entity, short-term liquidity levels, differences in the type of businesses of banks and controlling for characteristics of the loan, such as the maturity or the amount, among other factors. The centrality measures with the largest impact are those based on degree and strength, with closeness centrality in the second place. These results indicate that it is profitable for the entities to establish a higher number of interconnections in the network in order to become more central, given that this behavior contributes to the achievement of better interest rates compared with the market average. In a market like this, which is not too concentrated and which is prone to show relatively high and volatile nominal interest rates, securing bilateral rates close to 2% higher than the market average constitutes a substantial spread that improves the financial revenues of the entities.

8. Concluding remarks

This paper presents the first comprehensive network analysis of the topological structure of the Argentine unsecured interbank market, commonly known as call market. It represents one of the most relevant places where financial entities conduct, on a daily basis, the management of their liquidity positions, and, because of that, the interest rates settled in this market provide a key reference for the determination of the other longer-term rates of the economy. There are not many papers in general about this particular Argentine market, so the present piece of research is intended to enrich the current understanding of its structural features and, though tangentially, of the changes and fluctuations it underwent over the years under analysis.

In general terms, the Argentine interbank network is characterized by its relatively modest size, both in terms of its number of nodes and edges. It is not the smallest interbank network analyzed so far in the world, but its scale is not comparable to the largest empirical networks of other countries. The Argentine network exhibits low density, as is usual in these types of graphs, and a reciprocity nearly always above the levels of a random network (with the same degree of completeness). The average distance between entities is quite short, with a mean lower than 3.

The network is prominently disassortative, which means that highly interconnected nodes tend to establish more links with low-degree nodes. This behavior is common in absolutely all the empirical interbank networks studied over the world. But it is worth noting that in the case of Argentina the graph's disassortativity decreased after the global crisis, compared with the levels witnessed between 2003 and 2007. Additionally, the network displays a higher clustering coefficient than a random network, in line with the interbank loans networks of other countries.

In the Appendix it can be found a Table which compares the topological metrics of the different empirical interbank networks analyzed so far around the world, to the best of our knowledge, using methodological techniques similar to the ones applied here. This survey is useful to trace the main contrasts and similarities between the abundant and heterogeneous studies within this literature in constant expansion. For instance, it can be inferred from the survey that the networks based on payment systems and those based on balance sheet exposures tend to be bigger and denser than interbank loans networks. Additionally, they often show, on average, higher clustering coefficients than the latter. As part of a future research agenda, a cross-country regression analysis constitutes a potential enriching exercise that could be performed on the basis of this type of information.

When focusing on the time dynamics of the Argentine case, it is possible to note that there is a certain correspondence between the movements in the size of the network and the economic activity in the country. On the other hand, it was found that the number of edges reacts with a positive and high elasticity to changes in the number of nodes in the network (Figure 7). This finding contradicts many theoretical models that assume a constant average degree in networks that grow in size over time.

Between 2003 and 2007 the Argentine network grew sharply, according to all of its topological metrics. However, the subsequent outbreak of the global crisis in 2008 triggered a dramatic collapse. The graph's density experienced a drastic decline, reaching its minimum level in the series during the beginnings of 2009. Simultaneously, both the clustering and reciprocity coefficients decreased to levels comparable to those of a random network, as consequence of the significant contraction of the number of active edges in the market.

Once the crisis was left behind, all the structural indicators recovered swiftly in 2010-11 and they stabilized around those levels thereafter, until the end of the period under analysis. It is important to clarify that the 2010-11 recovery was qualitatively different from the growth of 2003-07. In the years after the global crisis, assortativity coefficients became less negative and the entities adopted an unusually high reciprocity, both phenomena that had not been evidenced during the previous expansionary phase. During the stage with the strictest FX controls (2011-15), the network remained stable, in line with the economic stagnation that has prevailed in the country since then, displaying topological indicators that did not experience significant modifications then in 2016-17. In these last years, only incipient changes in the trends of some metrics can be perceived, but not yet enough unambiguous to extract definite conclusions.

The main providers of liquidity in the network were SOBs (more clearly between 2004 and 2008) and DPBs. The latter group of banks also performed a more influential role as intermediaries than the former. That is, they constantly displayed a high number of both out- and in-degrees, acting, in average, as the most central entities of the market. SFBs represented the major liquidity borrowers throughout the period, while NBFIs always played a peripheral role in the network, switching roles between being net lenders or net borrowers alternatively over the years, and turning more clearly into liquidity borrowers during 2016 and 2017.

Regarding the degree distribution of the network, the evidence seems to support consistently the hypothesis that total degrees, in-degrees and out-degrees distributions fit better to a Lognormal than to a Power Law or to a Poisson. The most important implication of this finding is that those degree distributions seem to be heavy-tailed, so they would not be correctly characterized by a random graph. This means that a narrow group of highly connected entities coexists with a large number of low-degree entities. From a systemic risk perspective, this fact implies that the network tends to be "robust-yet-fragile", in the sense that it is resilient to random failures of its nodes, but it could be very vulnerable when facing directed attacks to the most central banks. This constitutes a key result to consider when designing macroprudential policies, given that it highlights the relevance of a rigorous detection of the most central agents, whose failures can potentially disrupt the systemic stability of the entire network.

The topological characterization presented in this paper posits solid empirical foundations to carry out theoretical exercises and simulations of shocks, both particularly for the Argentine network and for analogous markets in general of similar countries (i.e., with not very developed financial systems). The reported results are valuable to know more precisely to what extent the existing theoretical models about financial networks, contagion, cascade effects, etc. are applicable to the Argentine financial markets, and therefore to choose more adequately those that best fit to the Argentine case.

Complementarily, the effects of different node centrality measures on bilateral interest rates were examined by means of an econometric analysis, identifying a positive and significant impact, both in statistical and in economic terms. That is, central entities in the network tend to settle more convenient bilateral interest rates in their operations in the call market. Even controlling for the size of the entities (measured according to their assets or deposits), their liquidity levels, type of business, type of entity, characteristics of the loan granted (maturity, amount, etc.), the centrality displayed by a node in the graph explains a non-trivial effect on its capability to lend at a higher interest rate and borrowing funds at a lower cost. The most relevant centrality measures were those based on the degree and on the strength, explaining a rate differential between 1.1% and 1.7% with respect to the average market rate. In the second place, closeness centrality showed a stable and significant effect of nearly 0.5%.

These results highlight the relevance of taking account of the interconnectedness among financial entities and its evolution over time, both when examining the financial system from an aggregate perspective and also when approaching the banking business from a micro-level or entrepreneurial point of view. Considering the high domestic interest rates witnessed in Argentina and their volatility, profiting those rate differentials with respect to the average market rate on a daily basis constitutes a non-negligible source of revenues. These effects become even more relevant in a context of a BCRA focused on monetary aggregates to conduct monetary policy, as this policy regime tends to accentuate interest rate volatility (compared, for example, with a framework based on the determination of a certain monetary policy rate to manage the monetary conditions of the economy).

Given that very few studies about the Argentine call market, in particular, and about the different local financial networks, in general, have been carried out, the future research agenda is very broad. For instance, an enriching analysis would consist in performing simulations of the network's response when facing various shocks of different sources and intensities, and then evaluating potential structural changes that could be triggered by them. Also, it would be insightful to analyze more deeply specific stress events (particular days, weeks, or months of the Argentine history) to shed light on the dynamics of the graphs during those moments, detecting regularities or stylized facts that might be useful to strengthen the local systemic stability. Other studies could be based on other domestic networks, such as the payment system, for which the necessary data is not available yet, or the cross-holdings of financial assets by different agents. In this regard, more research is needed on domestic multilayer networks, an exponentially growing literature during recent years over the world (see, for example, Aldasoro & Alves, 2016). Finally, a dynamic analysis about the banks' successive trading activity and repeated interactions between pairs of them (in the vein of the study of Kobayashi & Takaguchi, 2017) could also provide valuable insights for subsequent theoretical modelling.

In conclusion, considering the interconnectedness among financial entities as a potential source of systemic risk leads to a fertile research agenda, with straightforward policy implications for financial regulators and monetary authorities. These topics emerged not only because of their key role during the global crisis of 2008-09, but also due to the increasing complexity of international financial systems. Thus, a thorough understanding of the potential externalities that can arise from those abundant interdependencies among financial (and non-financial) agents becomes a crucial task in a world where distances and reaction times are shortening at a striking pace.

9. References

- Akram, Q. F., & Christophersen, C. (2010). *Interbank overnight interest rates - gains from systemic importance*. Working paper Nº 11/2010. Norges Bank.
- Albert, R., & Barabási, A.-L. (2002). Statistical mechanics of complex networks. *Reviews of modern physics, 74*(1), 47-97.
- Albert, R., Jeong, H., & Barabási, A.-L. (2000). Error and attack tolerance of complex networks. *Nature, 406*, 378-382.
- Aldasoro, I., & Alves, I. (2016). *Multiplex interbank networks and systemic importance: an application to European data*. Working Paper Series Nº 1962. European Central Bank.
- Allen, F., & Gale, D. (2000). Financial Contagion. *Journal of Political Economy, 108*(1), 1-33.
- Alves, I., Ferrari, S., Franchini, P., Heam, J.-C., Jurca, P., Langfield, S., Laviola, S., Liedorp, F., Sánchez, A., Tavolaro, S., & Vuillemey, G. (2013). *The Structure and Resilience of the European Interbank Market*. Occasional Paper Series Nº 3/2013. European Systemic Risk Board (ESRB).
- Anastasi, A., Elosegui, P., & Sangiácomo, M. (2010). Determinantes de la tasa interbancaria de préstamos en Argentina. *Ensayos Económicos, 57,* 95-126.
- Barabási, A.-L., & Albert, R. (1999). Emergence of scaling in random networks. *Science, 286*, 509-512.
- Battiston, S., Delli Gatti, D., Gallegati, M., Greenwald, B., & Stiglitz, J. (2012). Liaisons dangereuses: Increasing connectivity, risk sharing, and systemic risk. *Journal of Economic Dynamics and Control, 36*(8), 1121-1141.
- Bech, M., & Atalay, E. (2008). *The Topology of the Federal Funds Market*. Staff Report Nº 354. Federal Reserve Bank of New York.
- Becher, C., Millard, S., & Soramäki, K. (2008). *The network topology of CHAPS Sterling*. Working Paper Nº 355. Bank of England.
- BIS. (2011). *Global systemically important banks: Assessment methodology and the additional loss absorbency requirement*. Basel Committee on Banking Supervision Consultative Document.
- Blåvarg, M., & Nimander, P. (2002). Inter-bank exposures and systemic risk. *Sveriges Riksbank Economic Review 2002, 2*, 19-45.

- Bonacich, P. (1972). Factoring and weighting approaches to status scores and clique identification. *Journal of Mathematical Sociology, 2*(1), 113-120.
- Boss, M., Elsinger, H., Summer, M., & Thurner, S. (2004). Network topology of the interbank market. *Quantitative Finance, 4*(6), 677-684.
- Bougheas, S., & Kirman, A. P. (2014). *Complex Financial Networks and Systemic Risk: A Review*. CESifo Working Paper Series Nº 4756.
- Bräuning, F., & Fecht, F. (2012). *Relationship lending in the interbank market and the price of liquidity*. Discussion Paper Nº 22/2012. Deutsche Bundesbank.
- Cepeda López, F. H. (2008). *La topología de redes como herramienta de seguimiento en el Sistema de Pagos de Alto Valor en Colombia*. Borradores de Economía Nº 513. Banco de la República. Colombia.
- Clauset, A., Shalizi, C. R., & Newman, M. E. J. (2009). Power-Law Distributions in Empirical Data. *SIAM Review, 51*(4), 661-703.
- Cont, R., Moussa, A., & Santos, E. B. (2013). Network Structure and Systemic Risk in Banking Systems. In J.-P. Fouque & J. A. Langsam (Eds.), *Handbook on Systemic Risk* (pp. 327-368): Cambridge University Press.
- Costa, L., Rodrigues, F. A., Travieso, G., & Villas Boas, P. R. (2007). Characterization of Complex Networks: A Survey of measurements. *Advances In Physics, 56*(1), 167-242.
- Craig, B., & von Peter, G. (2014). Interbank tiering and money center banks. *Journal of Financial Intermediation, 23*(3), 322-347.
- De Masi, G., Iori, G., & Caldarelli, G. (2006). A fitness model for the Italian Interbank Money Market. *Physical Review E, 74*.
- Degryse, H., & Nguyen, G. (2004). *Interbank exposures: an empirical examination of systemic risk in the Belgian banking system*. Working Paper Nº 43. National Bank of Belgium.
- Dijkstra, E. W. (1959). A note on two problems in connexion with graphs. *Numerische Mathematik, 1*(1), 269-271.
- Dorogovtsev, S. N., & Mendes, J. (2003). *Evolution of Networks*: Oxford University Press.
- Embree, L., & Roberts, T. (2009). *Network Analysis and Canada's Large Value Transfer System*. Discussion Paper 13/2009. Bank of Canada.
- Erdös, P., & Rényi, A. (1959). On random graphs. *Publicationes Mathematicae, 6*, 290-297.
- Finger, K., Fricke, D., & Lux, T. (2013). Network Analysis of the e-MID Overnight Money Market: The Informational Value of Different Aggregation Levels for Intrinsic Dynamic Processes. *Computational Management Science, 10*(2-3), 187-211.
- Freixas, X., Parigi, B. M., & Rochet, J. (2000). Systemic Risk, Interbank Relations, and Liquidity Provision by the Central Bank. *Journal of Money, Credit and Banking, 32*(3), 611-638.
- Fricke, D., & Lux, T. (2015a). Core-periphery structure in the overnight money market: Evidence from the e-MID trading platform. *Computational Economics, 45*(3), 359-395.
- Fricke, D., & Lux, T. (2015b). On the distribution of links in the interbank network: evidence from the e-MID overnight money market. *Empirical Economics, 49*(4), 1463-1495.
- Fruchterman, T., & Reingold, E. (1991). Graph Drawing by Force-Directed Placement. *Software – Practice & Experience, 21*(11), 1129-1164.
- FSB-IMF-BIS. (2009). *Guidance to Assess the Systemic Importance of Financial Institutions, Markets and Instruments: Initial Considerations*. Report to G-20 Finance Ministers and Central Bank Governors.

- Furfine, C. H. (1999a). *Interbank Exposures: Quantifying the Risk of Contagion*. Working Paper Nº 70. Bank for International Settlements.
- Furfine, C. H. (1999b). The Microstructure of the Federal Funds Market. *Financial Markets, Institutions & Instruments, 8*(5), 24-44.
- Gillespie, C. S. (2015). Fitting Heavy Tailed Distributions: The poweRlaw Package. *Journal of Statistical Software, 64*(2).
- Granovetter, M. S. (1973). The Strength of Weak Ties. *American Journal of Sociology, 78*(6), 1360-1380.
- Haldane, A. (2009). *Rethinking the financial network*. Speech delivered at the Financial Student Association. Amsterdam.
- Hüser, A.-C. (2015). *Too interconnected to fail: A survey of the interbank networks literature*. SAFE Working Paper Series Nº 91. Research Center SAFE - Sustainable Architecture for Finance in Europe, Goethe University Frankfurt.
- Imakubo, K., & Soejima, Y. (2010). The Transaction Network in Japan's Interbank Money Markets. *Monetary and Economic Studies, 28,* 107-150.
- Inaoka, H., Ninomiya, T., Taniguchi, K., Shimizu, T., & Takayasu, H. (2004). *Fractal Network derived from banking transaction - An analysis of network structures formed by financial institutions*. Working Paper Series Nº 04-E-04. Bank of Japan.
- Iori, G., De Masi, G., Precup, O. V., Gabbi, G., & Caldarelli, G. (2008). A network analysis of the Italian Overnight Money Market. *Journal of Economic Dynamics and Control, 32*, 259-278.
- Ising, E. (1925). Beitrag zur Theorie des Ferromagnetismus. *Zeitschrift für Physik, 31*(1), 253-258.
- Kobayashi, T., & Takaguchi, T. (2017). *Understanding the fundamental dynamics of interbank networks*. Discussion Papers Nº 1711. Graduate School of Economics, Kobe University.
- Kraenzlin, S., & von Scarpatetti, B. (2011). *Bargaining Power in the Repo Market*. Working Paper Nº 14/2011. Swiss National Bank.
- Limpert, E., Stahel, W. A., & Abbt, M. (2001). Log-normal Distributions across the Sciences: Keys and Clues. *BioScience, 51*(5), 341-352.
- Lozares, C. (1996). La teoria de redes sociales. *Papers, 48*, 103-126.
- Lublóy, Á. (2006). *Topology of the Hungarian large-value transfer system*. MNB Occasional Papers Nº 57/2006. Central Bank of Hungary.
- Machado, C. L., León, C., Sarmiento, M., Cepeda López, F. H., Chipatecua, O., & Cely, J. (2010). *Riesgo Sistémico y Estabilidad del Sistema de Pagos de Alto Valor en Colombia: Análisis bajo Topología de Redes y Simulación de Pagos*. Borradores de Economía Nº 627. Banco de la República. Colombia.
- Martínez-Jaramillo, S., Alexandrova-Kabadjova, B., Bravo-Benítez, B., & Solórzano-Margain, J. P. (2012). *An Empirical Study of the Mexican Banking System's Network and its Implications for Systemic Risk*. Working Paper 07/2012. Banco de México.
- Newman, M. E. J. (2002). Assortative mixing in networks. *Physical Review Letters, 89*(20).
- Nier, E., Yang, J., Yorulmazer, T., & Alentorn, A. (2008). *Network models and financial stability*. Working Paper Nº 346. Bank of England.
- Page, L., Brin, S., Motwani, R., & Winograd, T. (1999). *The PageRank Citation Ranking: Bringing Order to the Web*. Technical Report 1999-66. Stanford InfoLab.
- Pröpper, M., van Lelyveld, I., & Heijmans, R. (2008). *Towards a Network Description of Interbank Payment Flows*. DNB Working Paper Nº 177. De Nederlandsche Bank.

- Rendón de la Torre, S., Kalda, J., Kitt, R., & Engelbrecht, J. (2016). On the topologic structure of economic complex networks: Empirical evidence from large scale payment network of Estonia. *Chaos, Solitons & Fractals, 90*, 18-27.
- Rørdam, K., & Bech, M. (2009). *The Topology of Danish Interbank Money Flows*. Finance Research Unit, Department of Economics, University of Copenhagen.
- Sala, A., Gaito, S., Rossi, G., Zheng, H., & Zhao, B. (2011). *Revisiting Degree Distribution Models for Social Graph Analysis*. arXiv:1108.0027.
- Schumacher, S. (2017). Networks and lending conditions: empirical evidence from the Swiss franc money markets. *Journal of Network Theory in Finance, 3*(2), 69-101.
- Sheldon, G., & Maurer, M. (1998). Interbank Lending and Systemic Risk: An Empirical Analysis for Switzerland. *Swiss Journal of Economics and Statistics, 134*(4), 685-704.
- Sokolov, A., Webster, R., Melatos, A., & Kieu, T. (2012). Loan and nonloan flows in the Australian interbank network. *Physica A: Statistical Mechanics and its Applications, 391*(9), 2867-2882.
- Soramäki, K., Bech, M., Arnold, J., Glass, R. J., & Beyeler, W. E. (2007). The topology of interbank payment flows. *Physica A: Statistical Mechanics and its Applications, 379*(1), 317-333.
- Upper, C., & Worms, A. (2002). *Estimating Bilateral Exposures in the German Interbank Market: Is there a Danger of Contagion?* Discussion Paper 09/2002. Deutsche Bundesbank.
- van Lelyveld, I., & Veld, D. I. (2014). Finding the core: Network structure in interbank markets. *Journal of Banking & Finance, 49*, 27-40.
- Wasserman, S., & Faust, K. (1994). *Social Network Analysis: Methods and Applications*: Cambridge University Press.
- Watts, D. J., & Strogatz, S. H. (1998). Collective dynamics of ‘small-world’ networks. *Nature, 393*, 440-442.
- Wells, S. (2002). UK Interbank Exposures: Systemic Risk Implications. *Financial Stability Review*, 175-182. December.
- Wetherilt, A., Zimmerman, P., & Soramäki, K. (2010). *The sterling unsecured loan market during 2006–08: insights from network theory*. Working Paper Nº 398. Bank of England.

10. Appendix: Main topological measures of empirical interbank networks

Country	Reference	Period	Data type	Frequency	N	M[1]	Density	Reciprocity	Clustering[2]	Assortativity[3]	Average Distance	Degree distribution[4]
Australia	Sokolov *et al.* (2012)	2007	Interbank loans	Daily	55	69-83	2.6%	-	-	-0.1375	-	Rejects Power law
			Other interbank money flows		55	784-804	26.9%	-	-	-0.375	-	Rejects Power law
Austria	Boss *et al.* (2004)	2000-2003	Balance sheet exposures	Quarterly	883	Max. entropy	-	-	0.12 ± 0.01	-	2.59 ± 0.02	Power law (α=2.01)
Brazil	Cont *et al.* (2013)	2007-2008	Balance sheet exposures	Irregular	592-597	1,200	-	-	0.2	Disassortative	2.35-2.42	Power law (α=2.54)
Canada	Embree & Roberts (2009)	2004-2008	Payments	Daily	14	-	69.2% ± 3.3%	89.3% ± 2.5%	0.84 ± 0.015	-	1.31 ± 0.03	-
Colombia (a)	Cepeda López (2008)	2006	Payments	Daily	126	2,245	16.4%	34.2%	0.61	-	2.04	Power law (Out: α=3.06 / In: α=3.24)
Colombia (b)	Machado *et al.* (2010)	2006 and 2009	Payments	Daily	125-137	6,843-9,400	42.8%-60.6%	-	-	-	2.04-2.17	-
Denmark	Rørdam & Bech (2009)	2006	Interbank money market transactions	Daily	43.6 ± 4.1	75 ± 23	11.2% ± 5.8%	26.2% ± 5.5%	0.2 ± 0.1	-	2.9 ± 0.4	Exponential
			Payments		89 ± 5.3	283 ± 41	8.3% ± 0.8%	22.8% ± 1.8%	0.5 ± 0.1	-	2.5 ± 0.1	Negative binomial
Estonia	Rendón de la Torre *et al.* (2016)	2014	Payments	Yearly	16,613	43,375	13%	-	0.183	-0.18	7.1	Power law (α=2.45)
EU	Alves *et al.* (2013)	2011	Balance sheet exposures	Yearly	54	1,737	60%	71%	0.84	-0.24	1.38	Power law (α=3.5)
Germany	Craig & von Peter (2014)	1999-2012	Balance sheet exposures	Quarterly	1,732 ± 85	20,081 ± 1,461	0.66%	-	-	-	-	Rejects Poisson
Hungary	Lublóy (2006)	2005	Payments	Monthly	36	774	61%	-	-	-	-	-

Country	Reference	Period	Data type	Frequency	N	M[1]	Density	Reciprocity	Clustering[2]	Assortativity[3]	Average Distance	Degree distribution[4]
Italy (a)	De Masi *et al.* (2006)	1999-2002	Interbank money market transactions (e-MID)	Daily	140	200	-	-	$c(k) \propto k^{-0.8}$	$k_{nn}(k) \propto k^{-0.5}$	-	Power law (α=2.3)
Italy (b)	Iori *et al.* (2008)	1999-2002	Interbank money market transactions (e-MID)	Daily	177-215	-	-	-	-	Disassortative	-	Not scale-free, but heavier-tailed than a random network
Italy (c)	Fricke & Lux (2015a)	1999-2010	Interbank money market transactions (e-MID)	Quarterly	120-200	-	17%-25%	-	-	Disassortative	-	-
Italy (d)	Fricke & Lux (2015b)	1999-2010	Interbank money market transactions (e-MID)	Daily and Quarterly	-	-	-	-	-	-	-	Negative binomial (daily) Weibull (quarterly)
Italy (e)	Kobayashi & Takaguchi (2017)	2000-2015	Interbank money market transactions (e-MID)	Daily	94	303	-	-	-	-	-	-
Japan (a)	Inaoka *et al.* (2004)	2001-2002	Payments	Monthly	354	1,727	2.76%	-	-	-	-	Power law (α=2.1)
Japan (b)	Imakubo & Soejima (2010)	1997 and 2005	Payments	Monthly	444 and 354	1,383 and 1,709	1.4% and 2.7%	-	-	Disassortative	-	Power law (α=1.6-3.4)
Mexico	Martínez-Jaramillo *et al.* (2012)	2005-2010	Balance sheet exposures	Daily	27-40	280	30%	80%	-	Disassortative	1.7	Power law (α=3.5)
			Payments			471	40%	82%	0.7-0.85	Disassortative	1.5	Power law
Netherlands (a)	Pröpper *et al.* (2008)	2005-2006	Payments	Daily	129 ± 5	1,182 ± 61	7%	63% ± 2%	0.4 ± 0.02	Disassortative	2.0-2.5	-
Netherlands (b)	van Lelyveld & Veld (2014)	1998-2008	Balance sheet exposures	Quarterly	91-102	~1,000	8%	-	-	-	-	Rejects Poisson and Power law
Switzerland	Schumacher (2017)	2005-2012	Secured money market transactions	25-day periods	161	-	10%-20%	5%-10%	0.05-0.2	-	2-4	-
			Unsecured money market transactions		241	-	5%	20%-30%	0.1-0.3	-	2.6-3.7	-

Country	Reference	Period	Data type	Frequency	N	M[1]	Density	Reciprocity	Clustering[2]	Assortativity[3]	Average Distance	Degree distribution[4]
UK (a)	Becher *et al.* (2008)	2003	Payments	Daily	337	989	0.90%	-	0.23	-	2.4	-
UK (b)	Wetherilt *et al.* (2010)[5]	2006-2008	Interbank money market transactions	Daily	12-13	-	42.1%-38.5%	70.7%-68.9%	-	-	-	-
USA (a)	Soramäki *et al.* (2007)	2004	Payments	Daily	5,086 ± 128	76,614 ± 6,151	0.3% ± 0.01%	21.5% ± 0.3%	0.53 ± 0.01	-0.31	2.6 ± 0.2	Power law (α=2.11)
USA (b)	Bech & Atalay (2008)	1997-2006	Interbank money market transactions (federal funds)	Daily	470 ± 15	1,543 ± 72	0.70% ± 0.03%	6.5% ± 0.8%	In: 0.10 Out: 0.28	-0.06 to -0.28	In: 2.4 Out: 2.7	Out: Power law (α=2 ± 0.05) In: Negative binomial
Argentina	This paper	2003-2017	Interbank money market transactions	Monthly	65 ± 6	237.5 ± 73.1	5.5% ± 1.1%	7.9% ± 3%	0.19 ± 0.05	-0.16 ± 0.09	2.8 ± 0.5	Lognormal (μ=1.9 / σ=0.6)

Notes: 1) maximum entropy refers to a method used to estimate some exposures for which no disaggregated data is available, so the number of links does not emerge directly from the observed information; 2) $c(k)$ accounts for the number of triangles a node of degree k belongs to; 3) $k_{nn}(k)$ is a function that describes the average degree k_{nn} of the neighbors of a node with degree k; 4) α refers to the exponent of a Power Law, while μ and σ represent the mean and standard deviation of a Lognormal distribution, respectively; 5) Wetherilt *et al.* (2010) divided their analysis in two time phases: the first ranges from 18th May 2006 to 8th August 2007, and the second, from 9th August 2007 to 16th December 2008, so their results are reported here separately for each phase. This Table only reports the metrics explicitly mentioned or expressed by the authors of each paper.

Working Papers

2020

20/08 **Federico D. Forte:** Network Topology of the Argentine Interbank Money Market.

20/07 **Ángel de la Fuente:** Las finanzas autonómicas en 2019 y entre 2003 y 2019.

20/06 **Vasco M. Carvalho, Juan R. Garcia, Stephen Hansen, Álvaro Ortiz, Tomasa Rodrigo, José V. Rodríguez Mora and Pep Ruiz:** Tracking the COVID-19 Crisis with High-Resolution Transaction Data.

20/05 **Jinyue Dong and Le Xia:** Forecasting modeling for China's inflation.

20/04 **Le Xia:** Lessons from China's past banking bailouts.

20/03 **Ángel de la Fuente y Pep Ruiz:** Series largas de VAB y empleo regional por sectores, 1955-2018. RegData_Sect FEDEA-BBVA (v5.0_1955-2018).

20/02 **Luis Antonio Espinosa y Juan José Li Ng:**
ESP/ El riesgo del sargazo para la economía y turismo de Quintana Roo y México.
ING / The risk of sargassum to the economy and tourism of Quintana Roo and Mexico.

20/01 **Ángel de la Fuente:** La dinámica territorial de la renta en España, 1955-2018. Los determinantes directos de la renta relativa: productividad, ocupación y demografía.

2019

19/13 **Filip Blazheski and Adrian Casillas:** Tripping over the edge of the cliff – business and credit cycles, financial instability and recession triggers.

19/12 **Ángel de la Fuente:** La evolución de la financiación de las comunidades autónomas de régimen común, 2002-2017.

19/11 **Alfonso Arellano, Noelia Cámara and Diana Mejía:**
ING / Disentangling Vulnerability through Consumer Behavior: The Role of Financial Health.
ESP / Desentrañar la vulnerabilidad mediante el comportamiento del consumidor: el papel de la salud financiera.

19/10 **Ángel de la Fuente:** La liquidación de 2017 del sistema de financiación de las comunidades autónomas de régimen común.

19/09 **Guillermo Jr. Cárdenas, Luis Antonio Espinosa, Juan José Li Ng y Carlos Serrano:** La crisis por escasez de gasolina en México: un análisis de Big Data.

19/08 **Ángel de la Fuente:** Series largas de algunos agregados económicos y demográficos regionales: Actualización de RegData hasta 2018.

19/07 **Ángel de la Fuente**: La dinámica territorial de la renta en España, 1955-2016: una primera aproximación.

19/06 **Ángel de la Fuente:** Las finanzas autonómicas en 2018 y entre 2003 y 2018.

19/05 **J. E. Boscá, R. Doménech, J. Ferri and J. Rubio-Ramírez:** Macroeconomic Effects of Taxes on Banking.

19/04 **Santiago Fernández de Lis and Olga Gouveia:** Central Bank digital currencies: features, options, pros and cons.

19/03 **Santiago Fernández de Lis y Olga Gouveia:** Monedas digitales emitidas por bancos centrales: características, opciones, ventajas y desventajas.

19/02 **Santiago Fernández de Lis and Pablo Urbiola Ortún:** Digital transformation and competition in the financial sector.

19/01 **Santiago Fernández de Lis y Pablo Urbiola Ortún:** Transformación digital y competencia en el sector financiero.

CLICK HERE TO ACCESS THE WORKING DOCUMENTS PUBLISHED IN
Spanish and English

ENQUIRIES TO:
BBVA Research: Azul Street. 4. La Vela Building – 4th and 5th floor. 28050 Madrid (Spain).
Tel.:+34 91 374 60 00 y +34 91 537 70 00 / Fax:+34 91 374 30 25
bbvaresearch@bbva.com www.bbvaresearch.com