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Network structure and fragmentation of the Argentinean interbank markets[☆]

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ABSTRACT

This paper studies the network structure and fragmentation of the Argentinean interbank market. The unsecured (CALL) and secured (REPO) markets are examined, applying complex network analysis. Results indicate that although the secured market has fewer participants, its nodes are more densely connected than the ones in the unsecured market. The interrelationships in the unsecured market are less stable, making its structure more volatile and vulnerable to negative shocks. The analysis identifies two hidden underlying subnetworks within the REPO market: one based on the transactions collateralized by Treasury bonds (REPO-T) and the other based on the operations collateralized by Central Bank (CB) securities (REPO-CB). The changes in monetary policy stance and monetary conditions seem to have a substantially smaller effect in the former submarket than in the latter one. The connectivity levels within the REPO-T market and its structure remain relatively unaffected by the (occasionally pronounced) swings in the other market segment. Hence, the REPO market shows signs of fragmentation in its inner structure, according to the type of collateral asset involved in the transactions, so the average REPO interest rate reflects the interplay between these two partially fragmented submarkets. The REPO market's mixed structure entails one of the main sources of differentiation with respect to the CALL market.

1. Introduction

Interbank markets play a central role in financial systems. They are key to monetary policy implementation because they enhance the liquidity management operations of central banks (CBs) and financial entities. Complementarily, the interbank interest rates, which are generally short-term rates (usually, overnight), act as major references or benchmarks for the rest of the interest rates in the economy. Hence, the "price signals" that emerge from these markets constitute a leading indicator of the system's prevailing monetary conditions.

A significant distinction between different types of interbank markets lies in whether the operations are secured or unsecured, that is, if a collateral asset backs the transactions. If banks exchange liquidity on a secured basis, it means that the debtor entity grants other assets (e.g., government bonds) to guarantee the loan. In contrast, interbank loans are not backed by collateral in unsecured

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markets, so the risk involved in the operations is higher. This crucial difference has implications in terms of the interest rates and maturities of the transactions, as well as on the market's overall function. In addition, the secured interbank operations backed with government bonds and/or CB securities provide market liquidity and price reference for those instruments, contributing to the depth and development of the domestic bond market.

Despite their centrality and importance in the financial system, interbank markets are sometimes "fragmented." In the case of well-functioning and efficient interbank markets, there should be no difference between segments of the same market from an individual bank's risk perspective. However, the evidence shows that banks may face (risk-adjusted) differential funding costs or entry barriers in separate interbank market segments, which can have significant welfare costs (Gabrieli and Labonne, 2018). This fragmentation hinders the smooth transmission of monetary policy and, thus, impairs liquidity management and credit supply by affecting the funding capacity of banks and the price signals embodied by interbank rates. The absence of friction between different market segments is essential to reduce asset prices' volatility and to stabilize the economy, hence the relevance of properly detecting potential fragmentation *across and within* interbank markets, which policymakers and financial supervisors, in case of existence, should address.

The aim of this study is to assess the actual fragmentation of the interbank markets in Argentina, as well as the potential implications for monetary policy and financial stability. For this purpose, we go beyond the heterogeneity in interest rates faced by individual banks and apply network analysis methods to examine the underlying topological structure of the Argentinean markets. This approach allows for the detection of structural differences between or within the markets, divergent dynamics of key topological measures, or dissimilar reactions across market segments when facing specific contexts or events, which could entail evidence of market fragmentation.

Hence, in this paper, the Argentinean interbank markets are interpreted as networks, where the nodes are the active financial entities, and the links are the loans among them. There are two main interbank markets in the country. The secured market is called the REPO market, and the unsecured market is known as the CALL market. The Central Bank of Argentina (Banco Central de la República Argentina, BCRA) intervenes only in the REPO market. CALL and REPO interest rates represent important benchmark rates in the domestic financial system. Previous studies described the markets' main basic characteristics. For instance, Anastasi et al. (2010) analyzed the effect of interbank relationships on access to liquidity, focusing on CALL market; Forte (2020) analyzed the fundamental aspects of the unsecured market's network topology; and Elosegui and Montes-Rojas (2020) studied the effect of local and global network measures on the interest rate spreads, finding heterogeneous effects in both markets. Based on a novel comparative analysis of the topological structures of the secured and unsecured markets (and their coevolution over time), our main contribution in this paper is to provide evidence on the existence of fragmentation *between* and/or *within each* market, resorting to graph theory and network analysis techniques.

The interbank markets can be understood as complex networks that connect numerous banks and other financial institutions through different types of exposures.[1] In addition, these interactions take place in secured and unsecured interbank markets, which have different institutional frameworks and procedures. Moreover, they differ in market entry conditions and may be affected by particular market and banking regulations, if not different taxation treatments.

In our approach, we make use of the relevant literature on network fragility. The distribution of the interconnections across the agents in a network has meaningful implications in terms of its stability and potential systemic risks. For instance, a financial network structure characterized by a high concentration of connections among a few banks is subject to significantly different risks than a network in which the interconnections are more evenly distributed across participants.

Therefore, we analyze the empirical network degree distribution corresponding to the different segments of the Argentinean interbank market from 2015 to 2018, which allow us to draw conclusions on their comparative structures and evolution through different contexts. For analytical purposes, we not only distinguish the CALL market from the REPO market but also examine the inner structure of the latter thoroughly: we examine how its network structure changes when the CB operations are excluded, and how it changes when different types of collateral assets are involved (CB securities or Treasury bonds). The approach provides a new perspective on how Argentinean banks interact in each segment and how regulations and market structures affect such behavior, with potentially relevant implications for aggregate interest rates in the markets and prudential regulation, liquidity management, and financial market development. The analysis underscores the presence of two "hidden" underlying subnetworks within the REPO market according to the type of collateral involved in the operations. Both submarkets react differently to equal contexts or monetary policy interventions, with low co-movement levels in some volatile periods. Changes in the monetary policy stance and monetary conditions seem to have a substantially different effect in each submarket. The REPO market's mixed structure is one of the main drivers of the intermittent noncorrelation with respect to the CALL market topological measures and interest rates.

For a better understanding of the potential fragmentation, the network fragility in the different segments of the interbank market is assessed by studying the underlying characteristics of their network structures. We approximate the theoretical distribution that better fits the empirical degree distribution for the unsecured and the secured markets. With that objective, we apply the methodology developed by Clauset et al. (2009). This paper extends Forte's (2020) results about the CALL market's degree distribution, which proved to be more compatible with a lognormal than with Poisson or power law distributions.[2] This aspect tends to be particularly relevant in markets where interbank liquidity is traded predominantly in unsecured markets or in secured markets but with potentially

[1] Prudential regulations emphasize the importance of monitoring the degree of interconnectedness among banks to prevent potential macrofinancial risks and financial instability (BCBS, 2018).

[2] Random networks' degree distributions tend to follow a Poisson (or exponential) distribution, and scale-free networks' degree distributions are best fitted by a Power Law distribution (Barabási and Albert, 1999; Albert and Barabási, 2002).

illiquid and/or risky underlying assets. Moreover, potential liquidity shocks or falls in a collateral's market value occasionally occur in these types of networks. In addition, the access and interaction of banks with markets having different degree distributions may reflect their adaptive behavior to the segmented interbank market operation.

The paper is organized as follows. Section 2 briefly reviews the literature on interbank networks and the theory behind the analysis of the degree distribution as a proxy of network fragility. Section 3 describes the institutional framework of the Argentinean interbank markets, considering the different segments and their characteristics. Section 4 presents the empirical network analysis of the unsecured and secured markets and outlines the main results. Finally, Section 5 discusses and summarizes the conclusions.

2. Network topology and fragility of interbank markets

There is a large literature that applies network analysis to study interbank markets and, more recently, has extended to capture the systemic exposure of financial institutions. As previously mentioned, the interbank network plays a key role in the financial system, and from a macroprudential perspective, understanding its topological structure is relevant for both the CB and the financial supervisor to determine its robustness and/or fragility to shocks. Complementarily, a network's relative fragility can be analyzed through the characterization of the underlying degree distribution.

Network analysis of the degree of interconnectedness in the financial system can inform policymakers on how regulation can prevent and/or reduce banking instability, as well as optimal bank resolutions mechanisms. Hence, empirical networks have been used for stress test exercises.[3] Network centrality measures, developed to assess centrality in other contexts and markets and adapted to the context of financial networks, can guide policymakers in their evaluation of the systemic importance of financial and non-financial institutions.

A number of papers investigate the interplay between financial distress and topological characteristics of interbank networks, focusing on the network resilience to different kinds of shocks.[4] In the case of Argentina, Forte (2020) analyzed the network structure of the unsecured CALL market. The author found a short average distance between nodes and concluded that the market structure cannot be characterized as a random network. In this market, centrality variables lead to results compatible with the presence of embedded relationships among banks.[5] Although some authors argue that a more interconnected architecture enhances the system's resilience to the failure of an individual bank because credit risk is shared among more creditors, others suggest that a higher density of connections may function as a destabilizing force, facilitating financial distress to spread through the banking system. The overall picture that emerges from this literature is that the density of linkages has a non-monotonic effect on systemic stability, and its effect varies with the nature of the shock, the heterogeneity of the players, and the state of the economy. Thus, no optimal network structure that is more resilient under all circumstances can be identified.[6]

Network positioning could affect banks' interest rates through various mechanisms. First, in line with Acemoglu et al. (2015), dense interconnections serve as a mechanism for the propagation of shocks, leading to a more fragile financial system. As such, banks that are more connected may be perceived by the market as fragile. The same banks can be perceived as *too-interconnected-to-fail*, such that rather than being fragile, those banks are perceived as more likely to be bailouts.[7] This is similar to the *too-big-to-fail* effect observed in other interbank markets. Second, as argued by Booth et al. (2014), financial institutions with more extensive and strategic financial networks can more efficiently acquire and process information due to better access to order flows. Third, banks with higher centrality within the network have better access to liquidity and are able to charge larger intermediation spreads; see, for instance, Temizsoy et al. (2015), (2017).[8]

The structure of interbank networks has been mapped for several countries, where the topology of interbank markets has been characterized and stylized facts and regularities have been identified.[9] The most common findings reported in this literature are (i) interbank networks are sparse; (ii) degree and transaction volume distributions are fat-tailed, revealing heterogeneous players characteristics; (iii) the networks show disassortative mixing with respect to the bank size, so small banks tend to trade with large banks and vice versa; (iv) clustering coefficients are usually quite small; (v) interbank networks satisfy the small-world property[10]; and (vi) interbank networks have a tiered structure with a tightly connected core of money-center banks to which all other periphery banks connect.

[3] See Upper (2011) for a comprehensive review.

[4] See Iori et al. (2006), Nier et al. (2007), Gai et al. (2011), Battiston et al. (2012), Karik et al. (2012), Lenzu and Tedeschi (2012), Georg (2013), Roukny et al. (2013), Acemoglu et al. (2015).

[5] Indeed, in a previous work, Anastasi et al. (2010) reported similar empirical results for the same market.

[6] For a survey on systemic risk and financial contagion, see Chinazzi and Fagiolo (2013).

[7] See, for instance, Battiston et al. (2012).

[8] Previous empirical evidence from Angelini et al. (2011), Bech et al. (2010), Temizsoy et al. (2017) suggest that being systemically important, by size or connectedness, can explain part of the cross-sectional variation in banks' borrowing costs before and during the global financial crisis.

[9] Examples include Boss et al. (2004) for the Austrian interbank market; Soramaki et al. (2007) and Bech and Atalay (2010) for the US Federal funds market; De Masi et al. (2006), Iori et al. (2008), and Fricke and Lux (2015) for the Italian-based e-MID; Degryse and Nguyen (2007) for Belgium; Craig and Von Peter (2014) for the German interbank market; Langfield et al. (2014) for the UK; and in Veld and van Lelyveld (2014) for the Dutch market. Billio et al. (2012) studied the time-series properties of interconnectedness measures in financial markets.

[10] A network is *small-world* if the mean geodesic distance between pairs of nodes is small relative to the total number of nodes in the network, that is, this distance grows no faster than logarithmically as the number of nodes tends to infinity.

In the specific case of Latin American countries, the interbank networks of Brazil (Silva et al., 2016; Souza et al, 2014; Tabak et al, 2014; Cajueiro and Tabak, 2008) and Mexico[11] are the most extensively analyzed, but recent papers have studied the interbank markets of Bolivia (Caceres-Santos et al., 2020), Colombia (León and Renneboog, 2014; León and Miguelez, 2021), and Perú (Cuba et al., 2021). There are some contrasts between the region's different networks, mainly related to specificities of each banking system, such as foreign currency exposures and/or their size/depth. However, all of them share relevant network characteristics: a core-periphery structure, disassortative mixing, short average distances, and clustering coefficients, which entail useful indicators of systemic risks. Nevertheless, the concept of fragmentation has not been addressed with the approach implemented in this paper, which could be easily applied to other Latin American or emerging countries to assess this phenomenon in their respective interbank markets.

The study of the markets' network structure provides some key insights about their stability when facing different shocks. This issue leads us to another important literature strand related to the empirical degree distribution of the network, which is one of the most important elements that define the system's underlying topological structure.

In random networks, the nodes' degree distribution tends to behave similarly to a Poisson (or exponential) distribution, but scale-free networks are better described by a power law (Albert and Barabási, 2002). A fat-tailed degree distribution (e.g., the power law or the lognormal) implies that in such a network, a few highly connected nodes coexist with a myriad of low-connected agents. This fact has strong implications in terms of the system's resilience, as those networks can be characterized as *robust-yet-fragile* structures (Albert and Barabási, 2000). Networks are surprisingly resilient against random errors; that is, to random failures or removals of a large number of nodes (robustness), even when the networks are faced with high failure rates. However, this error tolerance is coupled with a high weakness to targeted attacks to the network's most central nodes, as it rapidly breaks into isolated fragments when a few of the most connected nodes are removed (vulnerability). In contrast, networks that do not have such strong dominant central nodes tend to be more resistant to targeted shocks. In fact, random graphs present this converse risk structure. They easily absorb targeted attacks but tend to fall apart rapidly with random failures. This happens because those networks do not have particularly central nodes of systemic relevance that provide cohesion to the network structure.

Hence, in the context of interbank networks, this attribute has key implications regarding the assessment of systemic fragility and potential risks. If an empirical financial network displays a fat-tailed behavior, then a rigorous identification of the central agents in the graph should become a priority task for CBs and regulators.

In terms of market fragmentation, it is interesting to note that Gabrieli and Labonne (2018) showed that in the case of European banks in the 2011–2015 period, the fragmentation in the interbank market was mainly explained by two sources: idiosyncratic bank risk and sovereign-dependence risk. In 2011, the ECB announced interventions with open market operations in secondary government bonds markets, the so-called Outright Monetary Transactions on sovereign debt securities. Because of the increased secondary market liquidity and the ECB implicit collateral, the fragmentation in the interbank market declined. In fact, the sovereign and idiosyncratic risks identified by the authors were reduced by these two factors.

In this paper, we apply the statistical procedure developed by Clauset et al. (2009) to assess which is the theoretical distribution that best fits each market network's empirical degree distribution. The authors consider the relative relevance of different fat-tailed distributions for the degree distribution at hand. For instance, the most crucial consequences of the Power Law or the lognormal degree distribution derive from the fact that they are fat-tailed, compared to Poisson or Exponential distributions. Considering that issue, the authors test other types of fat-tailed distributions in addition to Power Laws, not limiting themselves just to the latter alternative. These distributions show histograms with a slower decay, compared to an exponential distribution, as the variable of interest increases (in our case, the node degree):

$$\lim_{x\to\infty} \frac{f(x)}{e^{-x}} \neq 0. \tag{1}$$

Therefore, to assess the network fragility in the Argentinean interbank market, we identify the theoretical distribution that best fits the empirical degree distribution of the secured and the unsecured markets. In addition, we examine potential differences *within* the REPO market, including or excluding the BCRA from the network. Finally, we investigate if structural differences arise when considering the operations using Treasury bonds as collateral or those backed by BCRA securities. Results showing significantly different empirical distributions in the markets may be not only an indication of different risks from the macroprudential point of view but also evidence of market fragmentation in the interbank market.

3. The Argentinean interbank markets

During the period under analysis (2015–2018), the Argentinean banking system was comprised of 76 banks.[12] The five main banks concentrated 50% of the total credit, and most of them actively participated in the interbank market (71 in the unsecured and 52 in the secured segment). The interbank market can be understood as a complex network, in which the interaction between banks

[11] Martínez-Jaramillo et al. (2014) characterized the Mexican interbank network; Molina-Borboa et al. (2015) and Poledna et al. (2015) studied the multilayer network of exposures among Mexican banks, including interbank credit, securities, foreign exchange, and derivative markets, and Usi-Lopez et al. (2017) analyzed the repo market in that country.

[12] Including 12 public banks (two national, nine provincial, and one municipal), 33 domestic banks, nine foreign banks, seven branches of foreign banks, and 15 non-bank financial entities. Source: BCRA.

and the BCRA[13] determines relevant reference interest rates for the economy (the unsecured or CALL rate and the secured or REPO rate), in deep interaction with the CB's reference monetary policy interest rate.[14] The monetary policy is transmitted through the interbank interest rate to all the interest rates of the financial system (deposit rates, loan rates, and others), affecting the economic activity level and/or the inflation rate.

The unsecured or CALL market is an over-the-counter market, in which banks can informally transact bilaterally and directly.[15] The participants have counterparty exposure limits that frame the bilateral transactions, subject to the general limits imposed by CB regulations. The transactions are cleared on the Medio Electrónico de Pagos (MEP) platform of BCRA.[16] Most of the activity is concentrated in overnight loans, with only a small number of transactions maturing beyond three days (the weekends or extended holidays). Most of the banks, including the smaller and specialized ones, operate in this market. In fact, some of them only have access to the CALL market and do not operate in the REPO market. As mentioned before, the CB does not operate in the market's unsecured segment. The overnight CALL rate is published by BCRA, and it is a traditional benchmark rate for the financial market.

On the other hand, the secured or collateralized market (i.e., REPO market) functions through the electronic trading platform SIOPEL of the Mercado Abierto Electrónico (MAE).[17] Only banks and financial entities that are members (or adherents) to MAE can participate in this platform, which explains why this market has significantly fewer participants compared to the CALL market. The platform is anonymous and bilateral with all positions visible by the participants. It is an order-driven system with no market-making arrangements. The transactions are not settled through a central clearing counterparty, and each participant establishes counterparty limits, although the credit risk is limited by the use of collateral (treasury and/or CB securities) and haircuts.[18] In fact, the system is settlement-risk free because there is an online validation of the portfolio limits for each transaction between the parties.

The BCRA actively participates in the secured market through its lending and deposit facilities called "*Pases*" (the active transactions—loans to banks—are known as REPOs, but the deposit facilities used by financial entities are called "reverse REPOs"). Additionally, the CB conducts open market operations (non-systematic and sparse). The BCRA issues its own debt securities to absorb or provide liquidity from/to the market, affecting the economy's interest rates and monetary conditions.[19]

Hence, for analytical purposes, the REPO market in Argentina can be divided into different segments, according to the participating agents and the type of asset involved as collateral, including transactions: (i) settled by banks and the CB, (ii) between banks (excluding the CB) secured with Treasury bonds, and (iii) between banks (excluding the CB) secured with CB securities.

Fig. 1 summarizes the interbank interest rates and BCRA´s policy interest rates during the period. The CB REPO and reverse REPO interest rates define an "interest rate corridor." In general, CALL and REPO interest rates are located within the corridor limits. However, for the analyzed period and during several episodes, the interbank interest rates crossed the rate corridor limits. It can also be noted that the REPO secured market interest rate is usually below the CALL unsecured interest rate.

Fig. 2 shows the relative importance of each interbank segment. As can be seen, the market volume is mostly explained by the REPOs between banks and the CB. In this segment, most of the transactions are explained by reverse REPOs, a deposit facility used by the monetary authority to sterilize excess liquidity from the interbank market. In general, banks are not normally willing to participate in REPO operations (lending facility) as these transactions are considered a bad reputational sign for the market.[20]

On the other hand, Fig. 3 indicates the relative importance of the CALL vis-à-vis the bank REPO market (excluding the CB) during the period under analysis. It can be noted that the REPO market was more important than the traditional CALL market during most of the period.

The database includes 78,168 unsecured (CALL) and 150,296 secured (REPO) daily transactions from January 1, 2015, through December 31, 2018. Approximately 92% of the transactions in the CALL market and 98% in the REPO market were overnight. In the unsecured market case, we use information from the SISCEN CB database that includes operations among banks on a net daily basis, lender and borrow id (anonymized), volume, maturity, interest rate, and currency. On the other hand, the secured market

[13] The participant banks use the interbank market to negotiate temporary reserve positions (surplus or deficit), as well as securities (in secured markets), and to manage liquidity that may eventually be channeled to the nonfinancial sector. In addition, the BCRA's monetary (and FX) operations, carried out for the fulfillment of their objectives (including bonds operations, passive and active repos, open market operations, loans to financial institutions, and others) are implemented through debits and/or credits in the banks' current accounts affecting the same reserve positions and their minimum reserve requirements compliance.

[14] The cutoff interest rate of the primary issuances of the BCRA's securities, with the Central Bank's REPOs rates (deposit and credit facilities), are the reference or monetary policy rates in Argentina.

[15] See Elosegui and Montes-Rojas (2020) for a complete description and a network characterization of this market. In addition, the work by Anastasi et al. (2010) described the special role of bank relationships in this market.

[16] The MEP is a Real Time Gross Settlement (RTGS) platform. In addition, the net transactions are daily informed through SISCEN Information Task Requirement of the bank regulator (Superintendencia de Entidades Financieras y Cambiarias). The information of the CALL market used in this study comes from that source.

[17] The MAE is an electronic negotiation market created in 1989. It is the main electronic market for the negotiation of securities, foreign currency, and repos in Argentina.

[18] The collateral can be either treasury or central bank securities, and the haircut is calculated daily by MAE based on their volatility and liquidity, usually ranging from 10 to 30%. Usually, it is approximately 10% for government securities.

[19] 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. These securities were used until 2018, when another Central Bank debt instrument called LELIQ, with a 7-day maturity that can only be transacted by banks, replaced them.

[20] In fact, in the period under analysis, some of these operations were registered, but they were negligible: only 0.9% of total reverse REPO operations in the 2015–2018 period.

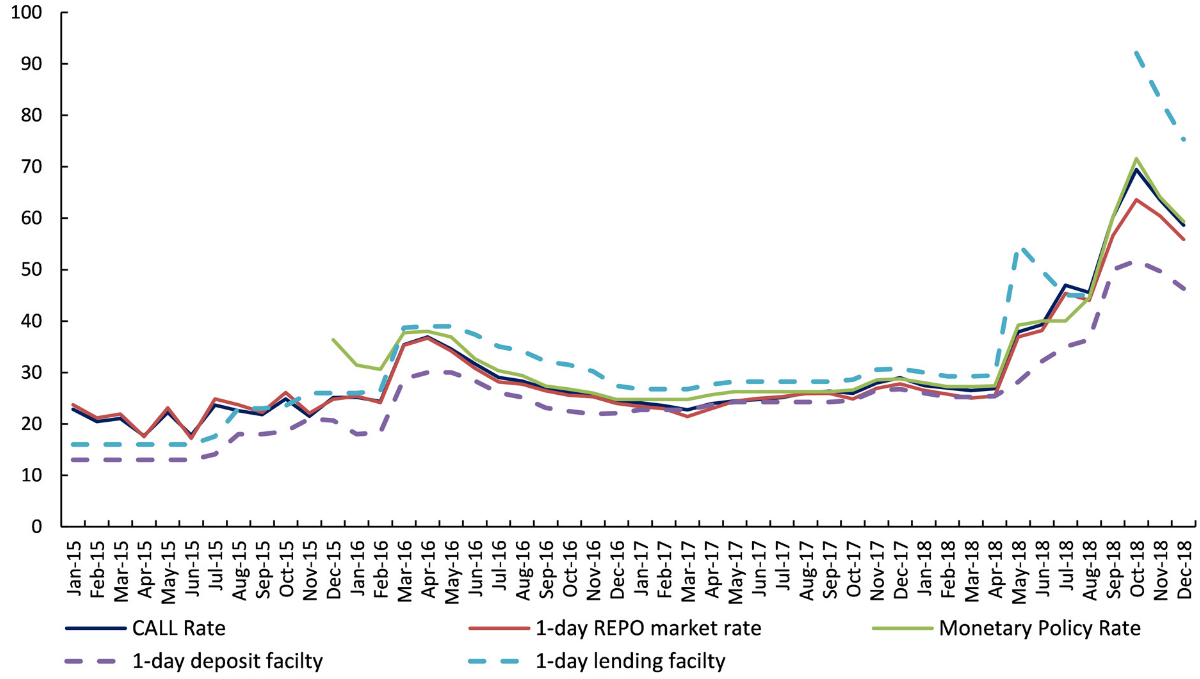

Fig. 1. Interbank interest rates and the Central Bank's interest rates rate corridors – in percentages.
Source: BCRA.

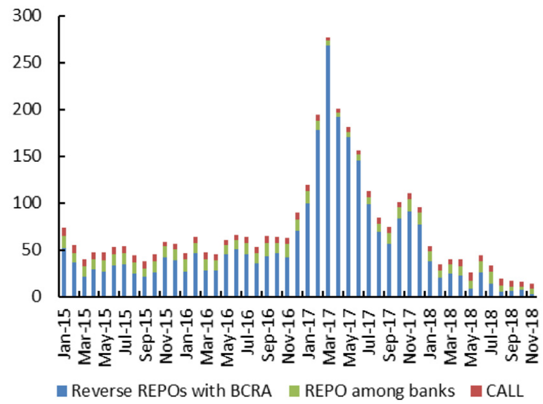

Fig. 2. Interbank Markets Volume.
- Monthly average of daily values in billions of $, constant purchasing power of 2018 -
Source: BCRA.

database includes daily information for each transaction pair in the MAE market, including the time of the transaction (hour, minute, and second), maturity and specific collateral (bond or security), volume, and implicit interest rate. To analyze the interest rate determinants in both markets, controlling for the relevant variables, we use a bank balance sheet database, a money market database (with interest rates and regulatory requirements), the current account balance at the CB, and the minimum liquidity requirement of each bank.

As can be seen in Table 1, a remarkable feature of the period under analysis is that it includes significantly different monetary policy regimes. In 2015, the first year of the sample, interest rate and capital account controls prevailed.[21] However, both types of controls were liberalized for the rest of the period. The government implemented an inflation-targeting regime using the interest rate as the main monetary policy instrument since 2016. By the end of the sample in October 2018, the BCRA implemented a monetary

[21] See, Forte (2020, p. 4).

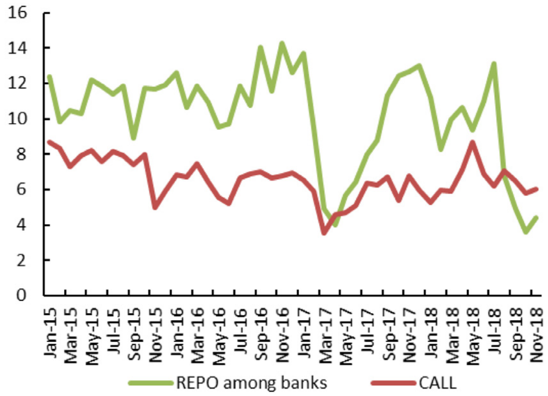

Fig. 3. CALL and REPO Markets Volume.
- Monthly average of daily values in billions of $, constant purchasing power of 2018 -
Source: BCRA.

Table 1
Main monetary and macroeconomic events in the period under analysis.

Period	Main Events
1 January 2015 - 16 December 2015	Capital controls, exchange rate restrictions, interest rate controls
9 August 2015	Primary presidential elections
25 October 2015	Presidential elections (1st round)
22 November 2015	Presidential elections (2nd round/Runoff)
10 December 2015	New Government takes office
17 December 2015 - September 2018	Inflation Targeting regime: progressive implementation
17 December 2015 - 31 December 2016	Removal of capital controls and interest rate liberalization
	Monetary Policy Rate: 35-day LEBAC (short-term CB securities)
January 2017 - September 2018	Monetary Policy Rate: 7-day REPO interest rate corridor (mid-point between deposit and lending facilities)
August - October 2017	Midterm elections (primary and general elections)
28 December 2017	Change in Inflation targets: triggers volatility in the exchange rate market
April 2018 - September 2018	Currency crisis: MPR increased 37.75 p.p. and the peso depreciated 50%
September 2018 - December 2018	Monetary policy regime change: Monetary aggregates control
	Main monetary policy rate: 7-day LELIQ (short-term CB securities)

base control monetary policy. The primary issuance of BCRA's securities[22] and their interest rates, together with the Pases' (active and passive) interest rate corridor, represented the monetary policy (or reference) rates between 2016 and 2018.

As previously mentioned, CB securities and Treasury bonds can be used as collateral assets in REPO market operations. The predominance of CB securities as the main monetary policy instrument is not the standard international practice, but it is more usual in emerging markets with underdeveloped local debt markets.[23] In the Argentine case, these securities represent banks' most important tool to manage its liquidity levels, and Treasury bonds are traded in the interbank markets with other objectives (e.g., as arbitrage transactions or to exploit carry trade opportunities).

As Fig. 4 shows, between 2015 and 2018, 38% of the REPO market operations had Treasury bonds as collateral, and the remaining 62% used CB securities. The CB was involved in 14.5% of transactions, nearly always using its own securities as guarantee. If these specific operations with the CB are not considered, Treasury bonds collateralized 45% of transactions carried out between commercial banks.

In practice, this could mean that nearly half of the REPO market transactions between banks (the ones collateralized by Treasury bonds) are settled with intrinsically different purposes than the other half (collateralized by CB securities, which are usually meant for liquidity management). In fact, the difference within the REPO market transactions also arises in terms of the bilateral rates settled in each type of operation, as shown by Fig. 5. The bilateral rates of the operations collateralized by Treasury bonds tend to be, on average, lower and more fat-tailed distributed than the transactions backed with CB securities are. Additionally, in the latter case, the interest rates are more concentrated around the mean interest rate.[24]

[22] The LEBAC or CB securities were used for monetary policy implementation during almost the entire period. In mid-August 2018, the BCRA initiated a LEBAC redemption and cancellation program. These instruments were replaced by "LELIQ" (see footnote 19). The redemption process was completed in December 2018. On August 7, the Monetary Policy Committee defined the LELIQ 7-day rate as the monetary policy rate.

[23] Rule (2011).

[24] One of the many reasons behind these differences is that in the REPO market, occasionally so-called special operations are settled, which are essentially securities-driven REPOs. In those cases, the agents are interested in the specific collateral asset, so they are willing to provide cheaper

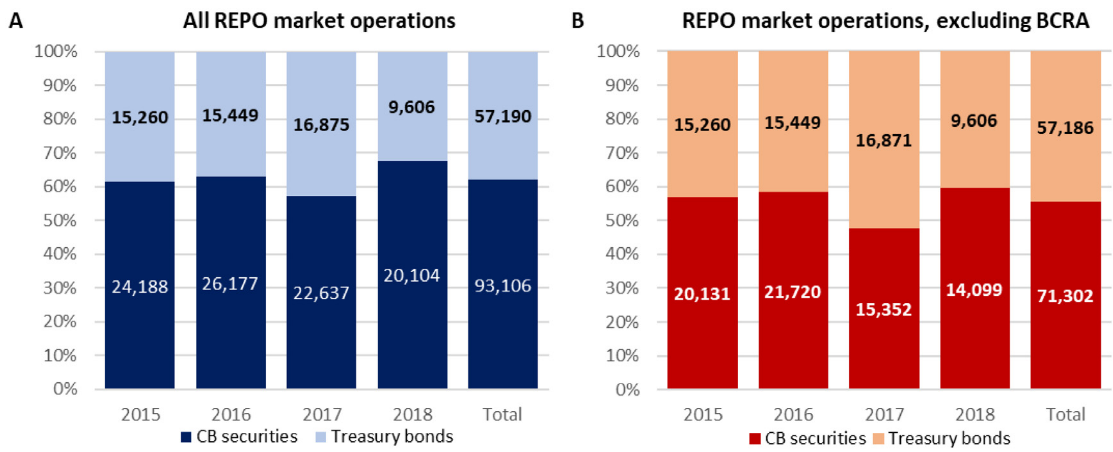

Fig. 4. Collateral assets used in the REPO market operations
Quantity of operations in which each type of collateral was used, as % of total number of operations during the year.
(A) Distribution of assets used as collateral in the REPO market. (B) Distribution of assets used as collateral in the REPO market, without considering the operations in which the CB was involved.

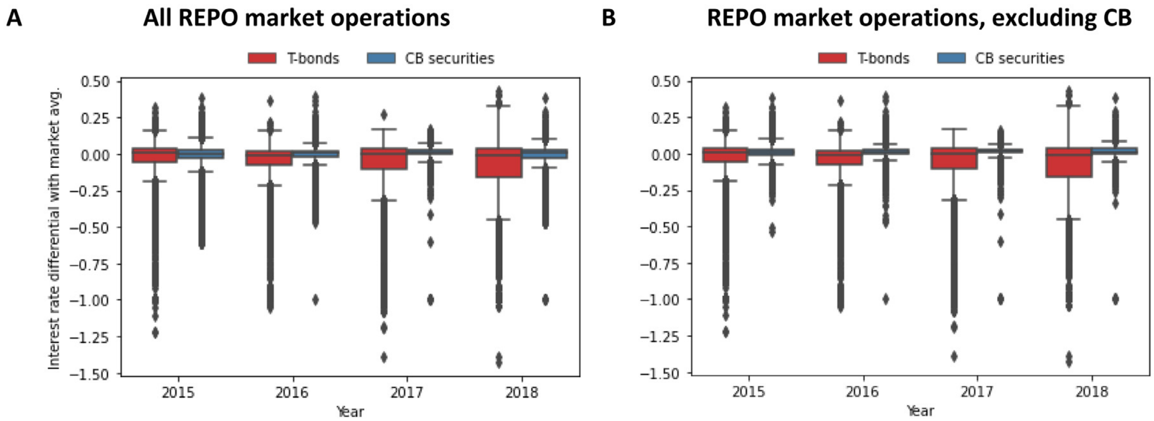

Fig. 5. REPO market: Interest rate differentials, according to the collateral asset.
(A) Distribution of the differences between the bilateral rates and the market average rate of the same day in the REPO market. (B) Distribution of the interest rate differentials, excluding the transactions in which the CB was involved (0 = T-bonds, 1 = CB securities).

The differences in liquidity conditions of the REPO transactions are statistically significant, depending on whether they have Treasury bonds or CB securities as collateral. To evaluate the difference, we consider a fixed-effects panel data regression model:

$$\boldsymbol{r}_{ijt} = \beta\ \boldsymbol{type}_{ijt} + \gamma\ \boldsymbol{X}_{ijt} + \mu_i + \delta_j + \theta_t + \varepsilon_{ijt}, \tag{2}$$

Where $\boldsymbol{r}$ is the interest rate of the overnight REPO transaction and ***type*** is a dummy variable that takes the value 0 if the collateral is a Treasury bond whereas it is 1 if it is a CB security. In addition, $\boldsymbol{X}$ is a set of control variables used in Elosegui and Montes-Rojas (2020) to control for liquidity requirements of lender and borrowers (we use the liquidity index defined as in Afonso and Lagos (2015) which is a measure of each bank's liquidity necessity), amount (logarithm of the volume of the transaction) and maturity (separate dummy variables for one, two, three or four days for the transaction).[25] The model has lender (i), borrower (j) and day-specific (t) fixed-effects and it is estimated for each month separately for the period January 2015 to December 2018. The model is thus a time-varying regression for which we are interested in the coefficient of the type of transaction. We also use a different specification where $\boldsymbol{r}$ is replaced by $\boldsymbol{ln(r)}$. The results are summarized in Fig. 6 for $\boldsymbol{r}$ (A panel) and $ln(\boldsymbol{r})$ (B panel).

liquidity to obtain it. As the Central Bank consistently intervenes with its own securities as collateral, the exceptionally far-from-the-mean bilateral interest rates usually appear when the collateralized assets are Treasury Bonds.

[25] In the case of Gabriele and Labonne (2018), the authors also regress an interest rate *spread* equation, considering the difference between the annualized (amount-weighted) average interest rate paid in interbank transactions and the deposit facility rate. They found that a larger exposure to higher sovereign risk was associated with higher spreads in their analysis.

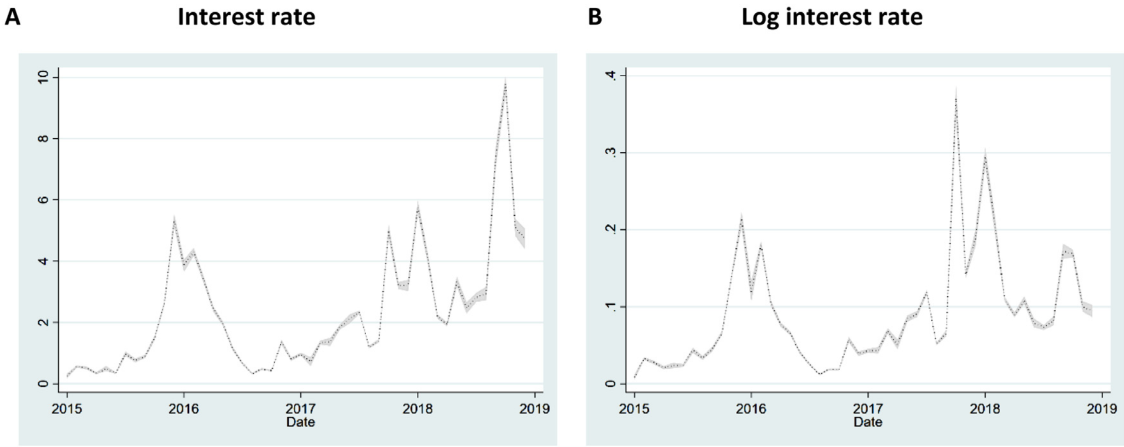

Fig. 6. Regression coefficient for interest rate differentials depending on the collateral.
Regression coefficient of the effect of a dummy variable (0 = T-bonds, 1 = CB securities) together with 95% confidence interval (robust standard errors clustered by day). (A) Dependent variable is the interest rate. (B) Dependent variable is the log rate.

Initially assuming no difference by type of collateral in 2015, the econometric results show that macroeconomic uncertainty and episodes of monetary policy tightening are associated with CB securities having a positive premium over Treasury bonds. For example, the 2015–2016 change of government at the national level (the official date is December 10, 2015) is associated with an average 5 percentage point premium or 15% higher interest rate. This spike reduces in the following months. The 2017 midterm elections and the government's announcements of changes in the inflation targets during December 2017 are also reflected in a higher premium. In 2018, Argentina suffered a severe currency crisis (the Argentinian peso lost 50% of its value that year), triggered by a sudden stop of capital inflows. Coincidentally, the larger premium change is observed in August 2018 (10 percentage points, 19% difference), precisely the month in which the exchange rate tensions peaked. Overall, the results show a positive premium for the entire sample, with larger differences in times of political uncertainty and macroeconomic volatility. A plausible interpretation of these results is that the transactions collateralized by CB securities are driven by intrinsically different purposes (e.g., liquidity management) compared to the operations secured with Treasury bonds (e.g., arbitrage opportunities).

In sum, the results indicate that changes in monetary conditions have a significantly different effect on the segment of CB-backed REPO transactions compared to the effect on Treasury-bond-secured transactions. This evidence points to the fact that the REPO market is fragmented according to the type of collateral involved in the transactions. In the next sections, we further analyze this divergence between the market segments, considering the underlying network distributions. As we will observe, the fragmentation of the markets is also reflected in significantly different underlying network distributions.

4. Empirical results

The interbank market can be represented as a directed network, where the nodes are the banks (including the BCRA, which only operates in the REPO market) and the links are constituted by the transactions among them in each of the markets. Following the usual practice, the direction of the flows is considered (therefore, an edge is incoming to the borrower and outgoing from the lender).

The network structures seem to exhibit differences not only between both markets (REPO vs CALL), but also *within* the REPO market (Fig.7). In the latter case, the structure of the interrelationships apparently differs depending on the participation of the BCRA and according to the collateral asset involved in the transactions (CB securities or Treasury bonds).

In the CALL market network, 64 ± 5 entities (N) established an average of 232 ± 49 links (M) on a monthly basis, whereas in the REPO market, only 49 ± 3 participants were involved, with 398 ± 70 edges (Fig. 8). The unsecured market always maintained a higher number of participants than the secured market did because barriers to entry were more restrictive in the latter. N remained stable in both markets between 2015 and 2017 but significantly fell since the beginning of 2018 (Fig. 8A).

The number of participants in the REPO market was on average 23% lower than it was in the CALL market, but nearly 72% more monthly links were created in the former. Hence, the connectivity levels in the REPO networks are significantly higher: The average degree of the nodes ($\hat{k}$) in the REPO market nearly doubles the average degree in the call market, whereas the density[26] levels in the former are three times higher than they are in the latter (Fig. 8-B and 8-C). Thus, although the unsecured market has more participants, it is not as well connected as the secured market is.[27] These conclusions do not substantially change when the operations with the CB are not considered. One plausible interpretation of this result is that the REPO market's secured transactions encourage

[26] The "density" (δ) of a network quantifies the percentage of the potential links that actually exist, given the number of nodes of the graph: $\delta = \frac{\sum_{ij} a_{ij}}{N(N-1)}$ (where a_{ij} is 1 if there is a link between bank i and bank j in the given network but 0 otherwise).

[27] These results are in line, for example, with those Schumacher (2017) obtained for the Swiss interbank markets.

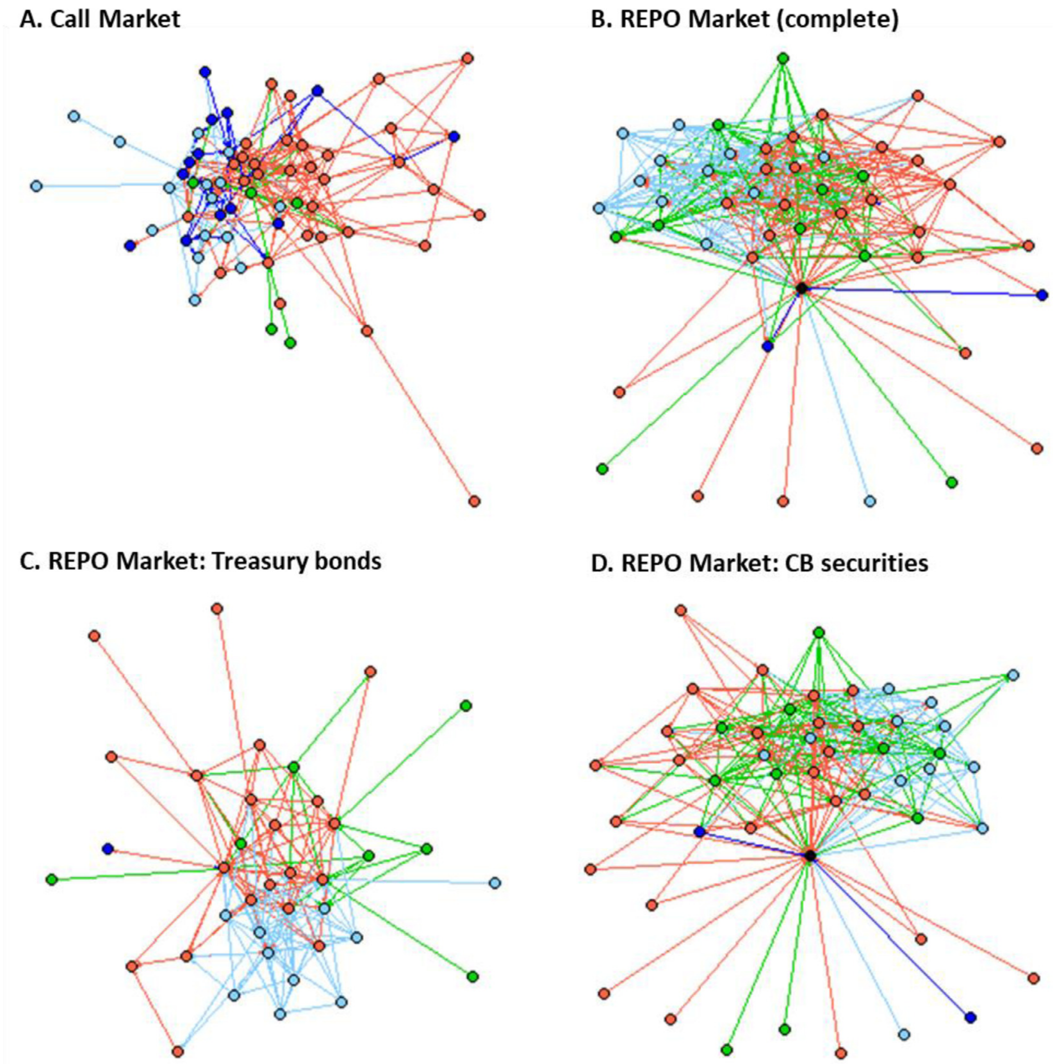

Fig. 7. Argentinean interbank markets: Network representations.
Each node represents a financial entity (green: state-owned banks; red: domestic private banks; light blue: subsidiaries of foreign banks; dark blue: non-bank financial institutions; black: CB). Each edge denotes the existence of at least one loan settled between a pair of entities during the month, and its color is defined by the lender entity. The monthly networks of June 2017 are depicted because the numbers of nodes and edges in that month were the most similar to the average of the period under analysis (CALL market: N = 65, M = 233; REPO market: N = 49, M = 380). Fig. 7-C and 7-D display the REPO market network, but only considering in each case the operations collateralized by Treasury bonds or CB securities, respectively. The visualization layout was computed using the Fruchterman-Reingold algorithm.

the establishment of connections between agents that do not necessarily know and trust each other. Instead, the unsecured market demands the creation of “trust” between the agents (after rigorous counterparty risk analysis) before establishing formal links. In addition, the blind electronic platform through which REPO market operations are conducted facilitates transactions among all the participants, whereas in the case of the CALL market, this type of marketplace is absent.

In addition, as can be seen in Fig. 8D, the clustering coefficient averaged 51% in the REPO market, substantially above that of the CALL market (16%). In fact, it always remained larger than the clustering levels that would emerge in comparable random networks of the same size.[28] The CALL market’s clustering coefficient was not only markedly lower but also fell sharply in 2018, even below the levels expected for a random network of the same size, simultaneously with the crisis that Argentina experienced that year. This result points to the conclusion that the lattice of interrelationships in the unsecured market is less stable than it is in the REPO market, particularly during hard times. Hence, the former market shows signs of being less resilient to negative shocks than the latter.

[28] The average clustering coefficient of a random network with N nodes and $\hat{k}$ average degree is equal to $\hat{k}$/N (Albert and Barabási, 2002).

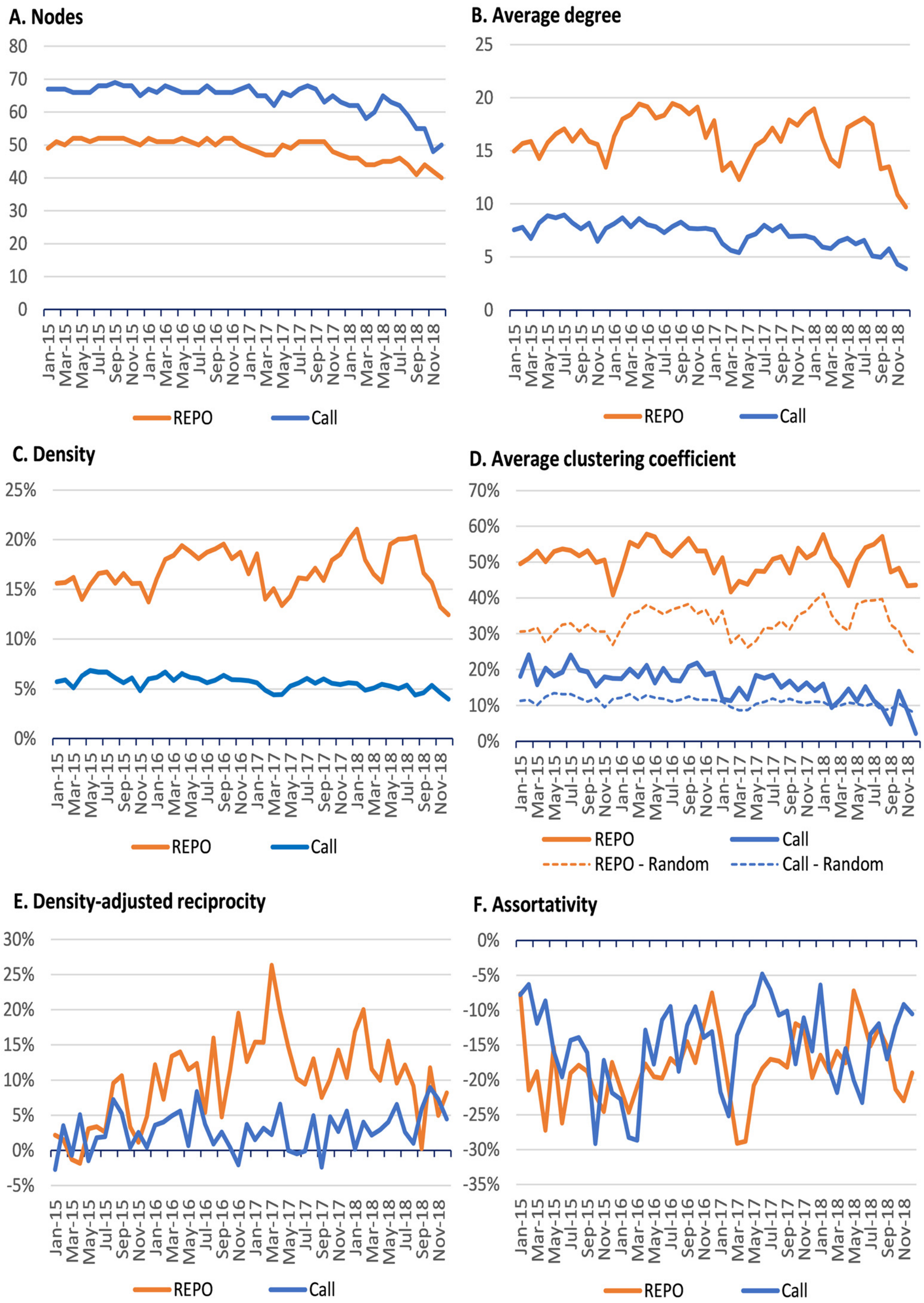

Fig. 8. Monthly topological indicators of the REPO and CALL market networks.
A. Number of participants in the network. B. Average total degree of the nodes. C. Density. D. Average clustering coefficient of the nodes in the network, and the expected clustering levels that would emerge from random graphs with the same number of nodes (N) and with the same average degree $\hat{k}$ (the average clustering coefficient of a random network is equal to: $\hat{k}$/N). E. Reciprocity levels adjusted by the density of the network: (reciprocity − density) / (1 − density) above 0 = greater reciprocity than a random network, below 0 = anti-reciprocal. F. Assortativity coefficient, computed using the Pearson correlation coefficient between the degrees of nodes that share links.

Table 2
CALL and REPO markets: percentage of monthly networks with a degree distribution that does not reject each null hypothesis.

	Call			**REPO total**			**REPO without BCRA**		
	Lognormal *p*>10%	Power Law *p*>10%	Poisson *p*>10%	Lognormal *p*>10%	Power Law *p*>10%	Poisson *p*>10%	Lognormal *p*>10%	Power Law *p*>10%	Poisson *p*>10%
2015	91.7%	91.7%	66.7%	91.7%	75.0%	75.0%	83.3%	91.7%	50.0%
2016	83.3%	66.7%	83.3%	100.0%	100.0%	75.0%	100.0%	91.7%	50.0%
2017	91.7%	75.0%	66.7%	83.3%	66.7%	75.0%	100.0%	91.7%	50.0%
2018	91.7%	83.3%	41.7%	91.7%	66.7%	91.7%	100.0%	75.0%	75.0%
Total	**89.6%**	**79.2%**	**64.6%**	**91.7%**	**77.1%**	**79.2%**	**95.8%**	**87.5%**	**56.3%**
Avg. Xmin	**4.4**	**9.1**	**10.4**	**11.5**	**21.2**	**24.0**	**12.4**	**20.2**	**19.9**

On average, both networks have greater reciprocity than comparable random graphs have, meaning banks tend to establish two-way relationships for reasons other than mere randomness (Fig. 8-E). However, the secured market shows higher reciprocity levels than the unsecured market, another indicator of the more embedded relationships in the former.

Because it is common in real-world financial networks (Forte, 2020; Hüser, 2015), both markets are prominently disassortative throughout the period (Fig. 8-F), which means low-connected banks are more likely to interact with high-degree banks than with other low-degree ones, and vice versa.

Nevertheless, the network structure of the REPO market can be understood as the result of two different underlying networks within that market: one derived from the interactions collateralized by CB securities and other that emerges from the transactions collateralized by Treasury bonds. From Fig. 7-C and 7-D, it is clear that both segments (or “submarkets”) present structural differences that deserve to be examined.

First, as mentioned in the introduction, the CB only operates in the REPO market and uses its own securities. The monetary authority is the main agent that defines liquidity levels in the market. Consistently, fewer entities participate in the REPO market using Treasury bonds (37 ± 3) than those using CB securities (48 ± 4; Fig. 9-A). The average degree of the nodes is higher in the network based on CB securities, especially during 2016 (Fig. 9-B). The connectivity levels in both segments, measured by the average density and clustering coefficient, remained similar throughout the period (Fig. 9-C and 9-D). However, the network based on Treasury bonds showed metrics that were more stable, whereas the market based on CB securities suffered several episodes of volatility; for example, September 2015 to January 2016 (in coincidence with the change of government ruling party), November 2016 to June 2017 (a period with a change in the monetary policy framework because the main reference instrument began to be REPOs instead of LEBACs), and 2018 (a period characterized by exchange rate volatility and a sharp reversal of foreign financial flows). Clustering levels always remained above those of a random graph of the same size. In both cases, the networks were disassortative, with comparable indicators in this regard (Fig. 9-F).

The most remarkable difference in the topological metrics is related to reciprocity: The network based on the transactions collateralized by Treasury bonds has high reciprocity, with banks establishing numerous two-way links, whereas, if the transactions collateralized only by CB securities are considered, the network turns out to be nearly neutral or even anti-reciprocal (Fig. 9-E). This fact is derived from the active presence of the BCRA and the related effect in terms of the network structure of that segment of the market.

As can be seen in Fig. 10, a preliminary analysis of the degree of network distribution reflects that the distributions are fat-tailed. After applying the tests Clauset et al. (2009) developed, it can be concluded that the lognormal distribution tends to be the one that best fits the empirical degree distributions of both the CALL and REPO market, outperforming the Poisson and Power Law distributions in the majority of the monthly networks (Table 1). The lognormal fit is not rejected in 89.6% of the cases in the CALL market, whereas in the REPO market, this hypothesis is not rejected in 91.7% of the cases. This result implies the degree distributions derived from both markets can be characterized as heavy-tailed. Therefore, they are composed of a few highly connected banks interacting with a myriad of less-connected entities, making both structures vulnerable to targeted attacks or failures of the main agents in the network. This result stresses the relevance of detecting and supervising the central nodes to improve the resilience of both networks.

When the transactions with the BCRA are not considered, the Poisson hypothesis is rejected in a higher number of months. This evidence points to the fact that the degree distributions of the networks *without* the BCRA are less similar to random graphs and more like fat-tailed graphs than in the case when all the market operations are considered. In fact, when the CB is not an active participant in the networks, the networks become more dependent on a few highly connected nodes. Therefore, as it would be expected, the segment that may be more vulnerable to the failure of its main participants is the one in which the CB is not involved.

Some conclusions from Table 2 are reinforced by the results shown in Table 3. The network based on transactions collateralized by Treasury bonds within the REPO market tends to reject de Poisson distribution as the best fit to its degree distribution in more cases than in the network based on CB collateral. The participation of the CB in the network, either directly or indirectly (through its liabilities used as collateral by entities) makes the network structure less similar to a pure fat-tailed distribution, smoothing the *robust-yet-fragile* aspect of that type of network and hence limiting that type of systemic risk to which the market is subject.

The results indicate that in the network of REPO operations collateralized by Treasury bonds, the key participation of central agents is relatively more important to the well-functioning of the market than it is in the case of the transactions backed by CB securities.

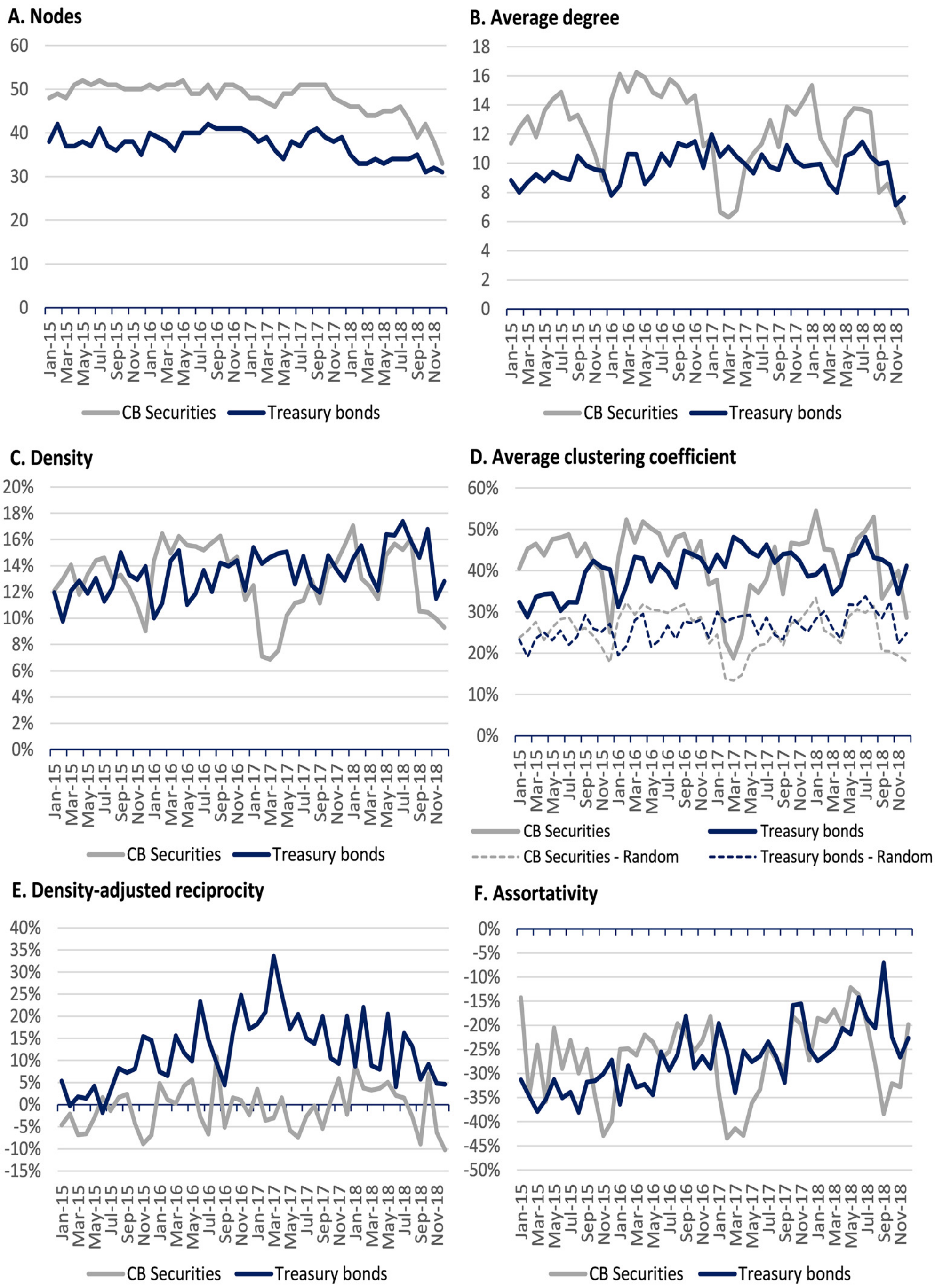

Fig. 9. Monthly topological indicators of the REPO market, distinguishing transactions depending on its collateral: CB securities or Treasury bonds. A. Number of participants in each subnetwork. B. Average total degree of the nodes. C. Density. D. Average clustering coefficient of the nodes in the network and the expected clustering levels that would emerge from comparable random graphs. E. Reciprocity levels adjusted by the density of the network (above 0: more reciprocal than a random network; below 0: anti-reciprocal). F. Assortativity coefficient.

Finally, to confirm these findings, we introduce an additional procedure to address the issue of detecting the best fit for each monthly degree of distribution. The procedure can be summarized in three steps:

(i) Apply the method described by Clauset et al. (2009) to the empirical degree distributions, as it was done in Tables 1 and 2.
(ii) If more than one theoretical distribution is not rejected, a classical Vuong test is performed to define which has the better fit.
(iii) If the Vuong test does not provide enough evidence to select one or another distribution, then the log-likelihood associated to each fit is compared to decide the better one.

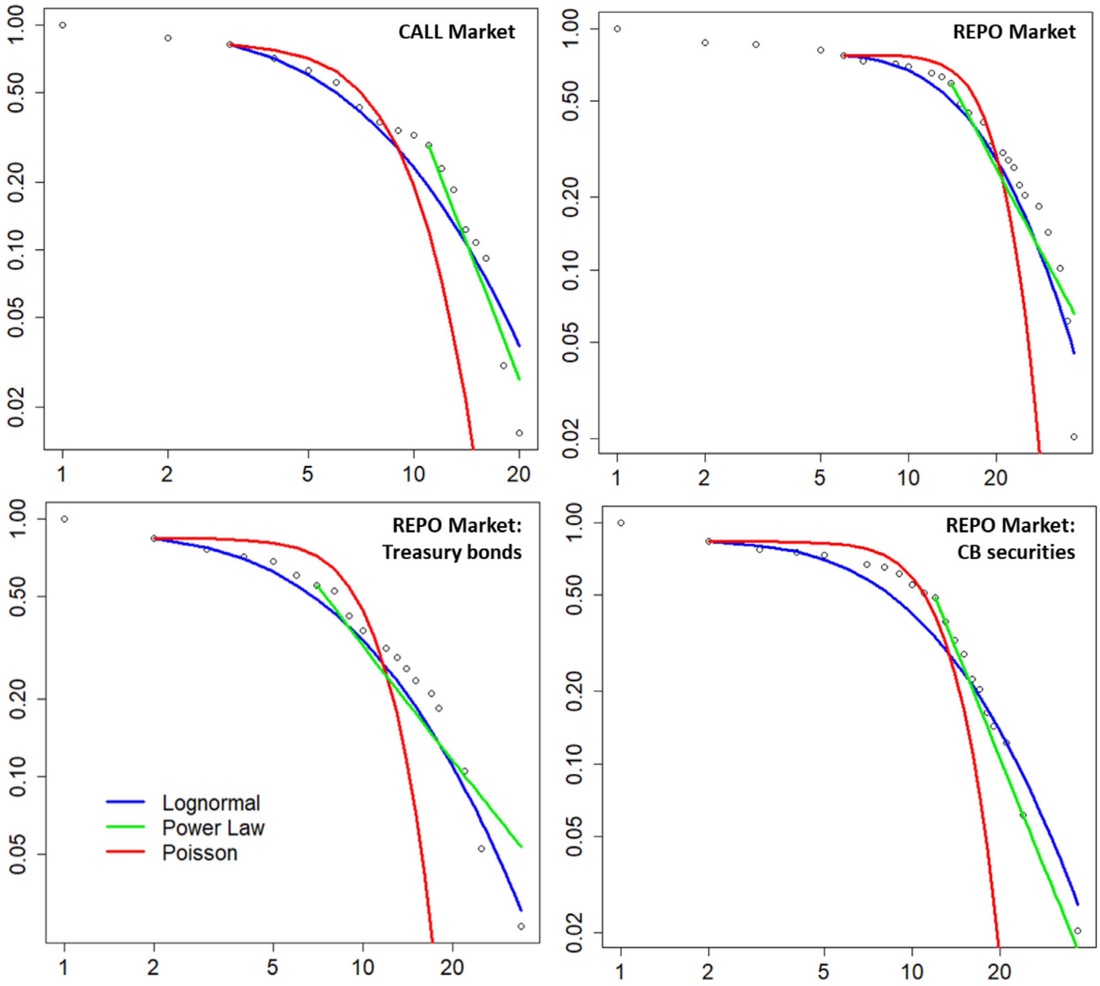

Fig. 10. Complementary cumulative distribution functions of the nodes' degrees.
Networks of June 2017, which were selected for the same reasons detailed in Fig. 7. The best-fit stylized distribution functions are depicted in each chart. Axes are in log-scale.

Table 3
REPO monthly networks, by collateral asset
Percent on which the distribution under the null hypothesis is not rejected.

	REPO - collateral CB			**REPO - collateral Treasury**		
	Lognormal *p*>10%	Power Law *p*>10%	Poisson *p*>10%	Lognormal *p*>10%	Power Law *p*>10%	Poisson *p*>10%
2015	91.7%	91.7%	91.7%	100.0%	100.0%	50.0%
2016	83.3%	100.0%	41.7%	91.7%	75.0%	41.7%
2017	100.0%	100.0%	50.0%	100.0%	83.3%	75.0%
2018	91.7%	83.3%	100.0%	83.3%	91.7%	75.0%
Total	**91.7%**	**93.8%**	**70.8%**	**93.8%**	**87.5%**	**60.4%**
Avg. Xmin	**11.6**	**17.4**	**15.1**	**4.3**	**11.5**	**12.4**

The results of this procedure for each (monthly) network of both markets are summarized in Fig. 11. The evidence reinforces the outperformance of the lognormal fit over the others. Considering the total period under analysis, the CALL market and the REPO market network structure does not differ significantly in this regard: In nearly 70% of the months, the best fit is achieved by the lognormal distribution, whereas in the other 30%, the Poisson distribution is better.

It should be noted that the REPO market network shows signs of having experienced a structural change during 2018 because its topology seems to have partially randomized in an economic period characterized by a balance of payment crisis and several

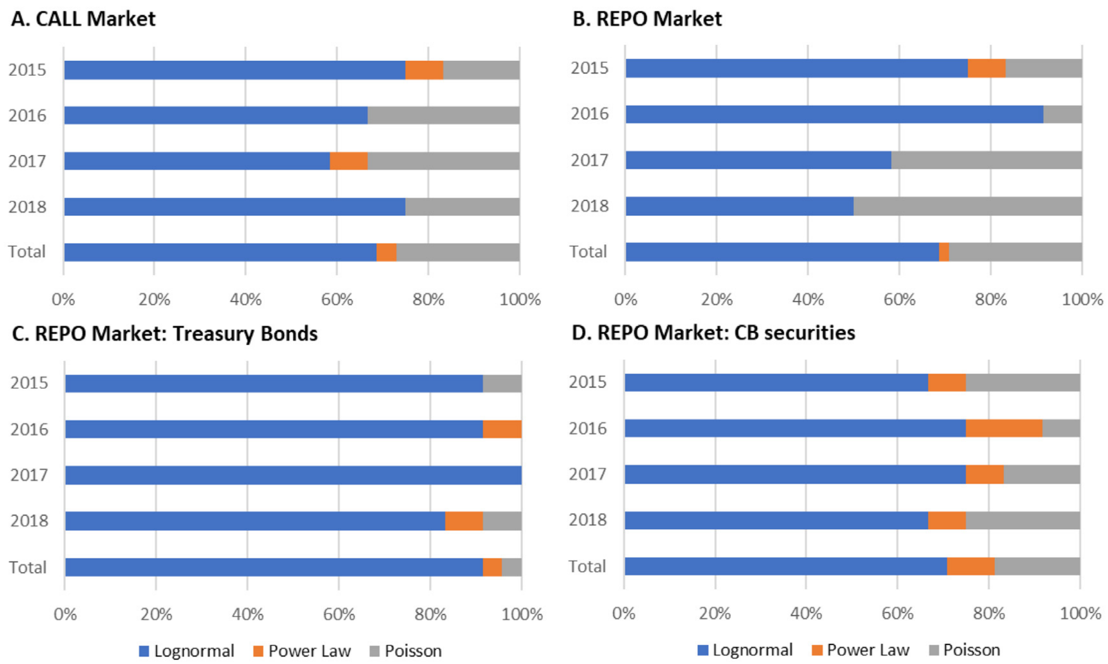

Fig. 11. Interbank (monthly) networks best described by each parametric distribution function (in percent of total months).

exchange rate depreciation episodes. Conversely, during the same period, the CALL market rejected the Poisson hypothesis most of the time. This result reflects that both segments reacted in different ways under similarly stressful events.[29]

Fig. 11-C and 11-D indicate that the network based on the REPO market transactions collateralized by Treasury bonds is significantly better described by fat-tailed distributions than the network based on CB-securities-backed transactions is. In fact, for the latter, the random network more often performed better in some cases. The difference has implications in terms of the fragility of these segments of the interbank market. The former is more vulnerable to the failure of its main agents, whereas the market based on CB securities seems to be slightly more resilient to these types of events. In the latter, the participation of the BCRA (directly or indirectly, through its securities) proves to be important in terms of stability.

5. Concluding remarks and discussion

This paper examines the secured (REPO) and unsecured (CALL) interbank markets of Argentina by applying a complex network approach to analyze market fragmentation. The empirical analysis is performed using a unique database spanning from 2015 to 2018, a particularly volatile period for the Argentinean economy.

Based on standard topological metrics (e.g., the average degree, density and clustering coefficients), it is found that although the secured market has fewer participants, its nodes are more densely connected than they are in the unsecured market. In addition, the interrelationships in the latter are less stable, as witnessed during the 2018 currency crisis, making its structure more volatile and vulnerable to negative shocks.

In general, the main topological indicators of the Argentinean interbank markets are in line with those found in other Latin American countries: disassortative behavior, relatively short average distances, low density levels, similar clustering coefficients and heavy-tailed degree distributions.

The analysis identifies two hidden underlying subnetworks within the REPO market: one based on the transactions collateralized by Treasury bonds (REPO-T) and the other based on the operations collateralized by CB securities (REPO-CB). The connectivity indicators were significantly more stable in the REPO-T market than they were in the REPO-CB segment because the latter is evidently more correlated with the liquidity swings defined by the CB. The changes in monetary policy stance and monetary conditions seem to have had a substantially smaller effect in the former than they have had in the latter submarket. Hence, the connectivity levels within the REPO-T market remain relatively unaffected by the (in some periods pronounced) swings in the other segment of the market.

The reciprocal relationships in the REPO-T segment occur with significantly more frequency than they do in the REPO-CB, showing that the BCRA's "one-way operations" in the REPO market crucially shape the type of relationships established in the latter subnet-

[29] The observed changes under a stress event may deserve better attention from the financial stability perspective that is beyond the present analysis.

work. Meanwhile, the fact that relationships have high reciprocity in the subset of transactions collateralized by Treasury bonds reflects that this subnetwork is significantly less affected by the participation of the BCRA in the REPO market.

In terms of financial stability, the distribution function that best fits the empirical degree distributions in both the secured and the unsecured market is the lognormal function, a fat-tailed distribution. As a result, the networks are composed of a few highly connected banks jointly with multiple entities with a significantly lower degree. Given this network structure, the highly interconnected banks are key to the stability of the markets, hence the regulation and supervision should focus on how well these central agents function to preserve the system's stability. However, the participation of the CB in the REPO market somewhat subdues this conclusion. When the transactions with the BCRA are not considered, the REPO market degree distribution becomes closer to a fat-tailed distribution, but when the transactions with the BCRA are considered, this conclusion is less categorical, and the Poisson hypothesis gains some support. This evidence implies that the CB's participation in the REPO market alters the structure and the underlying risks of the network. In this sense, the markets in which the CB does not intervene directly (the CALL market and REPO-T) would deserve different treatment from the point of view of financial stability supervisors. Nevertheless, it is important to note that the direction of the causality between the markets' risk structure and the CB's active participation (or not) is not straightforward. An extensive presence of the monetary authority in these markets could also undermine the development of a denser lattice of interrelationships among private entities, which could in turn mitigate the risks of a fat-tailed degree distribution in the networks.

Overall, these differences seem to reflect that the transactions collateralized with CB securities may have a motive that is different from those collateralized by T-bonds. In fact, the REPO-CB market appears to be more related to liquidity management activities, whereas the REPO-T market could be mainly motivated by arbitrage operations or the demand for specific bonds for various reasons, not necessarily related to liquidity management decisions.

The existence of two submarkets with different structures makes it difficult to interpret or extrapolate the full implications of the average interest rate that emerges from the REPO market. In fact, two very different types of decisions are condensed in that same price. In contrast, the unsecured CALL market is more homogeneous, with an interest rate reflecting a clearer reference of the "cost of money" in the financial system. This fragmentation of the REPO market has multiple implications. For example, the dichotomy posed by this fragmented market behind the formation of the REPO market interest rate jeopardizes the development of an interest rate forward market for this rate (or broader derivative markets of this rate in general), a pending task in Argentina. This issue could be solved if the CB computes (and publishes) an interest rate in an effort to capture the average rate of the operations that are settled only for liquidity management purposes, which should be near the monetary policy rate, defined by a specific (empirically defined) threshold. Such an indicator could be used as a reference to settle contracts, avoiding the biases introduced by, for example, special REPO market operations and/or arbitrage transactions derived from extraordinary conditions or attributes of specific collateral assets. These issues constitute an agenda for further research.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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