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Systemic risk and other interdependencies among banks in Bolivia

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journal homepage: www.elsevier.com/locate/lacbjSystemic risk and other interdependencies among banks in Bolivia[☆]Jonnathan Caceres-Santos^{a,*}, Anahi Rodriguez-Martinez^b, Fabio Caccioli^c,
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ABSTRACT

We performed a study of the Bolivian high-value payment system between 2015 and 2020 and of the network of interbank exposures between 2018 and 2020. We characterize the network structure of these systems and perform a systemic risk analysis. We find that the connectivity of the payment network has increased over time, and that it displays a core-periphery structure. Using the SinkRank algorithm, we identify two institutions as the most important throughout the period of study. However, by exploring daily, monthly and yearly networks, we find that, in general, the ranking depends on the level of temporal aggregation. Concerning interbank exposures, we carry out a systemic risk analysis using the DebtRank algorithm. In this analysis, we adjust the banks' Tier 1 capital to account for credit risk from the commercial loans portfolios, based on the estimation of unexpected losses. We find that average DebtRank and vulnerability of banks tend to increase over time. We link this to a corresponding trend in the size of exposures. We observe spikes in DebtRank and vulnerability, which also occur in correspondence with spikes observed in the size of exposures.

1. Introduction

The financial system in Bolivia has undergone an important transformation in recent years. The development of financial markets and the modernization of financial market infrastructures (FMIs), such as the high-value payment system, led to an increase on the level of interconnectedness among financial institutions.

In Bolivia, as in many other countries, the 2007 financial crisis showed the relevance of studying the increasing level of interconnectedness and taking into account contagion and systemic risk analysis and monitoring. In addition, financial systems have shown a fragility that affects the macroeconomic stability (Tymoigne, 2011). The consequences of the Lehman Brothers' default and the decision to rescue American Investments Group during the 2008 crisis made it clear that understanding interconnectedness in the financial system, designing adequate macroprudential policies, and developing adequate systemic risk metrics are important. In fact, these events suggested that, in addition to institutions that are "too big to fail", there are also institutions that are "too interconnected to fail". Similar to studies for Latin American countries, such as Colombia (Berndsen et al., 2018; León et al., 2018), Mexico (Batiz-Zuk

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et al., 2016; Martinez-Jaramillo et al., 2014), and Brazil (de Castro Miranda and Tabak, 2013). The studies on financial networks for the Bolivian case covered topics such as the elemental analysis of the high-value payment system (Cáceres and Aldazosa, 2013), the centrality of financial agents in the field of interbank electronic transfers (Cáceres, 2015), and the integrated analysis of the networks of bank-bank and bank-firm to approximate the effects of financial contagion (Cáceres, 2017).

In this paper, we study the interbank payment and exposure networks in Bolivia. For both networks, we aim to provide (i) a statistical characterization of the network topology and its evolution over time and (ii) a systemic risk analysis to quantify the stability of the system overall and to identify systemically important institutions. The combined analysis of these two aspects allows us to show the relationship between the evolution of the network topology over time and systemic risk.

There are many studies in which the network approach was used and proven to be useful when drawing important conclusions about payment systems; for instance: Bech and Atalay (2010); Bech et al. (2010); Becher et al. (2008); Bravo-Benitez et al. (2016), among many others. Here, we find that results depend on the level of temporal aggregation used in the analysis. As the level of aggregation increases, networks become denser, and more clustered, with a higher reciprocity. The change in the structure also reflects in the systemic risk analysis, which shows different rankings of systemic importance, measured by SinkRank (Soramaki and Cook, 2013), as the aggregation level changes.

One of the best-known network indicators of systemic risk associated with interbank exposures is DebtRank (Battiston et al., 2012). This was used originally to study the 1.2 billion USD given as emergency loans to the financial institutions by the Federal Reserve Bank during the 2008-2010 period. The DebtRank algorithm (Bardoscia et al., 2015; Battiston et al., 2012) is commonly used to estimate systemic risk in several banking and financial systems; for instance: Bardoscia et al. (2017); Battiston et al. (2016); Poledna et al. (2018, 2015), among many others. Here, we find that, in the last two years, the system showed an increase of systemic risk as measured by DebtRank, which we link to a corresponding increase in reciprocity and nodes' average strength. An additional feature of this work is that we adjust Tier 1 capital to account for unexpected losses that are related to their loan portfolios. In previous works, the applications of the DebtRank algorithm do not consider this adjustment. Nevertheless, we think that this adjustment is important, as one of the main functions of such capital is absorbing unexpected losses from banks' loan portfolios.

We also analyze the structure of the payment and exposure networks by identifying their backbones – subsets of links that are statistically significant due to the characteristics of the lenders and borrowers involved – with the methods proposed by Marcaccioli and Livan (2019) and Kobayashi et al. (2018). The result of this analysis suggests that the networks are largely random, as only a small number of links are validated once accounting for the activity of the nodes.

We organize the rest of the paper as follows: Section 2 explores the literature on financial networks and systemic risk measurement, whereas Section 3 describes the data used for the calculations. Section 4 introduces the methodological aspects of the paper, and Section 5 shows the most relevant results of this work. Finally, Section 6 concludes and explores further work.

2. Literature review

Financial networks are widely studied in the context of systemic risk, and their properties can have important implications in terms of financial stability (Battiston and Martinez-Jaramillo, 2018). For instance, it was shown that there is a trade-off between risk sharing via linkages to other banks and contagion risk due to linkages (Gai and Kapadia, 2010), which implies the possibility of a misalignment between individual and systemic risk.

The literature on financial networks has mostly focused on the statistical characterization of the topology of interbank systems and its impact on the propagation of shocks; for instance, Hüser (2016). More specifically, the empirical analyses of several national interbank systems showed that interbank networks tend to have a low density, characterized by heavy-tailed degree distributions and a high density of triangles (Bech and Atalay, 2010; Boss et al., 2004; Iori et al., 2008; Martinez-Jaramillo et al., 2014; Santos and Cont, 2010; Soramaki et al., 2007). We see that similar properties also hold for the payment and interbank exposures networks in Bolivia.

The consequences of these properties in terms of financial stability have also been considered from the theoretical point of view. For instance, Caccioli et al. (2012a) showed, in the context of a cascading model, that heavy tails in the distribution of degrees makes the system more stable with respect to the default of a random node but more fragile if a highly connected node defaults. Roukny et al. (2013) showed a similar result, arguing there is no optimal topology in terms of stability.

Another topological property, observed in several systems, is that interbank networks tend to display a core-periphery structure. This means that the network can be roughly considered a core of highly interconnected banks surrounded by peripheral banks that are poorly connected and mainly interact with the core, which effectively intermediates between peripheral banks (Craig and von Peter, 2014; Fricke and Lux, 2012; Martinez-Jaramillo et al., 2014).

In this respect, Hüser (2016) stressed that the number and magnitude of defaults following an exogenous shock depended on the network topology, and the fragility of the system depended on the location in the network of shocked institution. For instance, the failure of periphery banks is less damaging than the failure of core banks.

Banks interact in different markets and generate different types of exposures. For instance, banks issue securities that are later bought by other banks. By holding these securities, banks expose themselves to other banks. Foreign exchange transactions can also lead to large exposures between banks. These exposures are associated with settlement risk. Another market activity that can lead to considerable exposures is trading in financial derivatives. Furthermore, banks interact indirectly through the existence of common assets in their portfolios, Caccioli et al. (2012b). In this respect, part of the empirical literature has recently focused on the analysis of the financial system as a multilayer network; for instance: Martinez-Jaramillo et al. (2019); Poledna et al. (2015) and on the role of indirect connections between financial institutions, such as those due to overlapping portfolios, Poledna et al. (2020).

Our paper is clearly related to the literature on the Bolivian banking system. Cáceres (2015) used an eigenvector centrality as a selection filter for the main financial institutions in the interbank payment network. These entities were strategically connected, so they had a great capacity to distribute and contract funds within the network (core network). The author showed that liquidity contractions had a significant impact on second-line sources of liquidity and not on the first-line sources. More specific monitoring of central agents is needed by financial system regulatory entities, especially regarding their sufficiency and liquidity buffers.

Cáceres and Aldazosa (2013) analyzed three crises episodes in Bolivia that occurred in the period 2007-2010 by using a combination of network topology and simulation models to show that the participation of high-value payment system agents is not homogeneous (existence of central and peripheral agents). For classifying systemically important agents, the authors based the analysis on intermediation capacity, such as the concentration of the number of connections and the amount transferred. The main finding indicated a direct contagion to two financial entities, in which liquidity safeguards (funds and liquidity provision mechanisms) were sufficient to prevent the contagion from reaching greater proportions. They found that there were no possibilities of direct contagion due to the high levels of liquidity in the financial system. They identified two main factors of financial contagion in Bolivia: liquidity levels and their allocation.

Cáceres (2017), through the analysis of the bank-bank and bank-firm networks and simulation models, proposed a financial contagion model to estimate the exposure to credit risk for the banks in Bolivia and their unexpected losses derived from loans granted to groups of companies and non-collateralized interbank loans. Network tools have also been used for the characterization of other banking systems in Latin America, in particular in Colombia, Brazil, and Mexico.

Berndsen et al. (2018) examined the multiplex and the interaction of the Colombian financial networks. They noted the removal of modularity due to the integration of financial institutions multiplex networks with financial market infrastructures. Due to the positively correlated multiplexity, the aggregation of three single-layer financial institution networks maintained their modular scale-free architectures. Systemic importance of financial institutions could even be greater than analyzing a single layer because central financial institutions have a propensity to overlap across the financial network.

For the Brazilian case, de Castro Miranda and Tabak (2013) analyzed the interbank market and adapt the methodology presented by Battiston et al. (2012) using the DebtRank methodology and Merton's structural model. They found that the group of medium-sized institutions had the highest expected impact. The larger the institution, the higher the impact but lower the default probabilities. During the period, they pointed out a quite stable Brazilian financial system. On the one hand, the top 10 DebtRank financial institutions remained stable in the same period. On the other hand, only four of the financial institutions on a 1-year horizon had default probabilities above 1%.

For what concerns the Mexican banking system, Martínez-Jaramillo et al. (2014) measured and monitored systemic risk through topological metrics for payment system and interbank networks. The main findings were the wide range of empirical measures for two networks of the Mexican banking system: interbank exposures and the payment system flows. Additionally, the authors tested and provided good evidence of the robustness on financial networks of centrality measures. Also noteworthy, contagion was not necessarily related to asset size. The banks ranked high, in terms of interconnectedness, were important to determine the systemic importance in financial networks. Our paper also relates to the literature that tries to quantify to what extent financial networks are random.

Through the analysis of the Italian market for overnight loans e-MID, Finger et al. (2012) found evidence that the networks had a random behavior when analyzed with daily frequency information but had significant nonrandom characteristics for aggregate periods. The aggregations of time horizons showed that, for monthly and quarterly periods, the networks registered a high degree of structural stability.

Some network-based techniques have been introduced in the literature for the statistical identification of important backbone links by means of a network-based information filtering technique. In this paper, we use those introduced by Marcaccioli and Livan (2019) and Kobayashi et al. (2018).

Marcaccioli and Livan (2019) proposed a filtering methodology based on the Pólya urn approach in complex networks. They calibrated the model to extract statistically significant links (backbone) from a heterogeneous network. They identified the Pólya backbones of the US airport network using different values for the filter's tolerance to heterogeneity parameters, and they showed how the optimal value of such a parameter could be found using the maximum likelihood principle.

Kobayashi et al. (2018), to filter information with noise and nonessential elements that are generated in network systems, proposed a temporary filter to find the backbone. This filter allowed for finding significant edges and establishing relevant connections given the temporal interaction between nodes; this method was validated at different scales of interaction intensity.

3. Data

This section describes the data used to construct the weekly networks of interbank exposures and monthly networks of high-value payment systems. We first describe the data used for the payment system networks, and then we proceed to provide the details on the interbank exposure network. It is relevant to mention that we consider different periods for the two systems to show important changes in the structures of the two networks.

3.1. The Bolivian high-value payment system

The main payment system in Bolivia is LIP (Integrated Settlement of Payments). This system started operating September 8, 2014, replacing SIPAV (High-Value Payment System). Interbank transfers are settled with a hybrid scheme (real-time gross and deferred

net). Through this system, payments between financial institutions (interbank transfers) are settled, and the final settlements of other low-value (retail) systems that result from payments with checks, electronic cards, and electronic payment orders are made possible. It also enables the settlement of transactions made with dematerialized securities on the Bolivian Stock Exchange. The LIP system is managed by Central Bank of Bolivia; it processes approximately 329 million USD and 586 operations daily. On average, each operation is 0.6 million USD. The data cover the period from January 1, 2015, to February 28, 2020. We take into account daily frequency information on the value and the number of transfers aggregated between each pair of participants of the LIP system participants. We report some basic properties of the data in Figure 1 and Table 1.

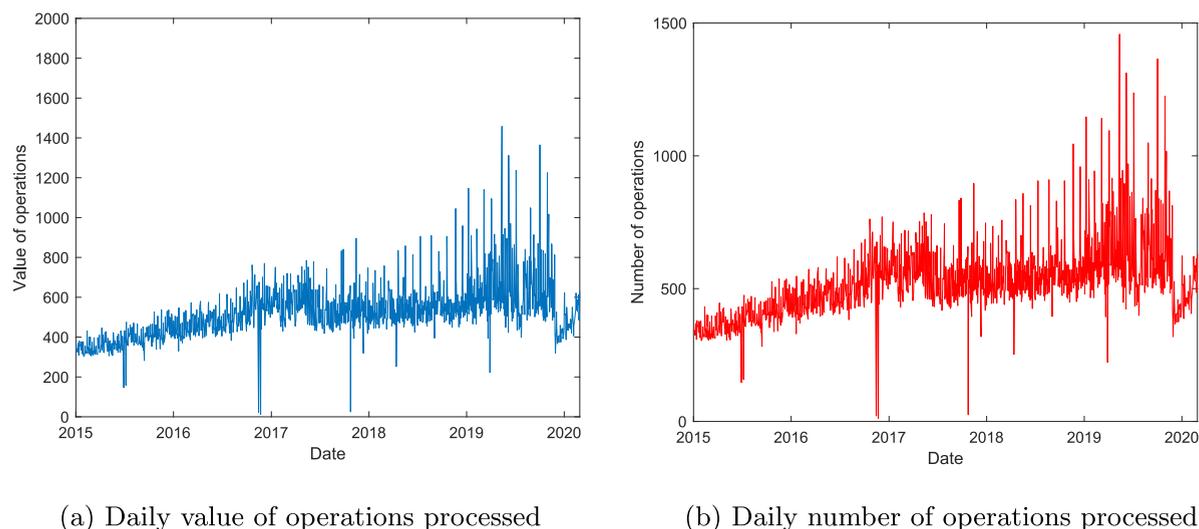


Fig. 1. Operations of Integrated Settlement of Payments

Table 1

Summary statistics of payment data (*expressed in millions of USD)

Statistic	Value of operations*	Number of operations
Mean	0.60	515.00
Median	0.09	503.00
Standard Deviation	5.06	132.14
Skewness	223.19	1.52
Kurtosis	62.586	9.93
Min./Max.	0.001/1433.63	12/1458.00

3.2. The Bolivian interbank exposures

The source of the data is the Central Bank of Bolivia. Interbank exposures comprise interbank credits (term equal to or less than 30 days) and interbank deposits (term greater than 30 days).

Interbank credits (call operations) are non-collateralized operations. They serve to cover immediate liquidity needs, and the negotiation conditions depend on trust and credibility between banks. Interbank deposits are fixed-term investment instruments for banks that have excess liquidity. The data cover the period from October 15, 2018, to February 24, 2020. For the analysis of interbank exposures, we take into account weekly frequency information from 43 banks.¹ We exclude those entities that do not trade interbank assets. The value of interbank loans and deposits, expressed in millions of USD ('x' axis in Figure 2), has a high volatility and a heterogeneous distribution (see Figure 2). We report the basic statistical properties of these data in Table 2.

¹ We use the term "bank" to refer to financial intermediary entities converting short-term liabilities to long-term assets.

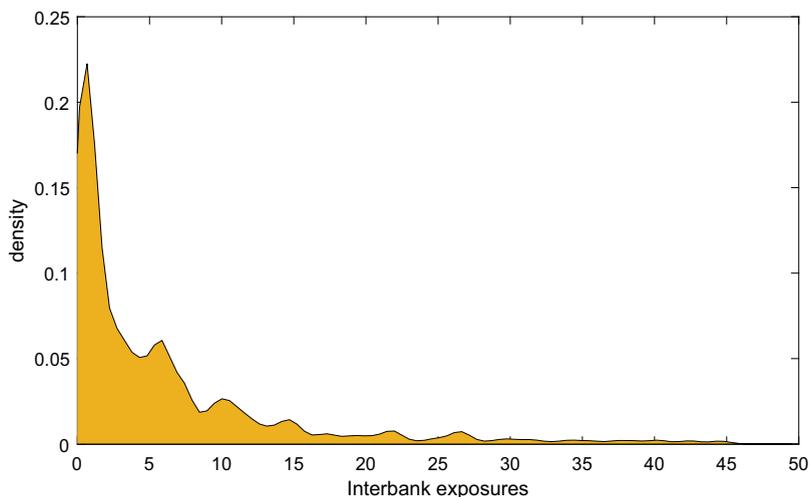


Fig. 2. Interbank Exposures Density Distribution

Table 2
Summary statistics of interbank exposures (* expressed in millions of USD)

Statistic	Value of operations*
Mean	5.81
Median	2.92
Standard Deviation	8.13
Skewness	2.36
Kurtosis	8.97
Min./Max.	0.002/47.57

4. Methodology

In this section we introduce some elementary notations and some of the methods used to study interconnectedness and its implications in the Bolivian financial system in two of its most relevant activities: the payments system and the interbank exposure network.

4.1. Basic concepts

We introduce some basic concepts first, and then we elaborate on the different approaches and methods used in our study.

A network is defined in terms of a set of nodes V and edges E , where element $E_{ij} \in E$ denotes the edge from node i to node j (the edge $i \rightarrow j$ is different from $j \rightarrow i$). This explicit connection scheme denotes a directed network. A weighted graph can be described as a graph with a weight $w(e)$ assigned to each edge (e).

Interbank connections are represented with an adjacency matrix A of size $N \times N$ (where N is the number of nodes), where $A_{ij} = 1$, if there is a link from banks i to bank j , while $A_{ij} = 0$ otherwise.

In Table 3, we define some network metrics that can be used to characterize the topology of a network.

Table 3
Summarizes some basic network concepts and definitions

Concept	Description
Degree	number of edges of a node
In-degree	number of incoming edges of a node
Out-degree	number of outgoing edges of a node
Average-degree	average number of connections of a node in the network
Triangles	connections among three nodes
Network size	number of nodes in the network
Completeness Index	number of observed connections/number of possible connections
Centrality	a measure of how central or important a node is in the network
Clustering coefficient	a measure of the density of connections around a node
Path	a set of nodes linked by edges
Loop	a closed path

4.1.1. Visualization of financial networks

Figure 3 shows two instances of the high-value payment system network. We can observe important changes in its structure over time, such as an increase in the number of nodes and in the density of the network. The larger nodes with a darker color tone have a significant systemic impact on the networks, as measured by SinkRank (Section 4.2), and dummyTXdummy-(their fall could lead to liquidity contractions). However, to capture such changes and effects more appropriately, we turn to other metrics.

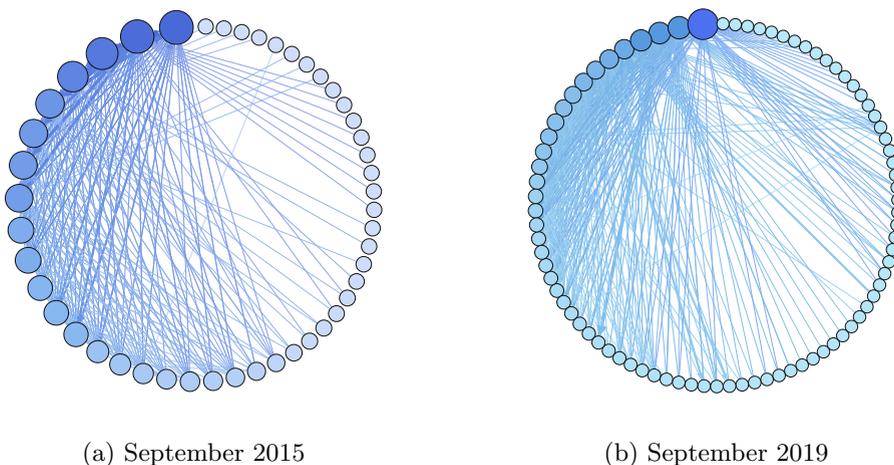


Fig. 3. Bolivian Payment Systems Network

For what concerns interbank exposures, the network changes according to the demand for liquidity in the market. Figure 4 shows two networks, the first one in normal conditions of liquidity demand and the second in unusual conditions of high liquidity demand, which causes a greater volume of interconnections between banks. Banks represented with larger nodes are systemically important (as measured by DebtRank, Section 4.2) in the network of exposures, given their strong interconnections causing a more than proportional effect to solvency risk on the other banks. The implications of changes in network states will be described through structural metrics and systemic risk measures.

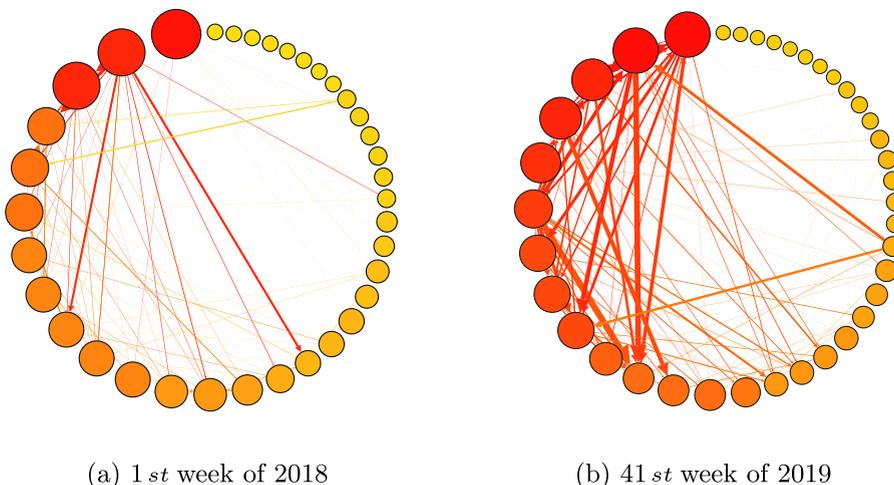


Fig. 4. Bolivian Interbank Exposures' Network

4.2. Structural and centrality metrics

In this section, we will describe some basic concepts related to graphs and networks. We use these concepts to develop the analysis for the payment system and the exposure analysis. We follow a similar notation to the one used by Martinez-Jaramillo et al. (2014).

Centrality metrics give important information to identify the more relevant institutions to financial stability and systemic risk monitoring. Some examples of centrality measures we use in this analysis are degree, strength, DebtRank and SinkRank.

4.2.1. Degree centrality

Degree centrality highlights nodes that are important because they have many neighbors, such as they can affect many nodes in the network. The degree centrality of a node is defined as the degree of the node.

$$C_d(i) = d_i \tag{1}$$

4.2.2. Reciprocity

In general $A_{ij} \neq A_{ji}$ in a directed graph. Reciprocity refers to the fraction of arcs in any direction for which there is an arc in the opposite direction, and it is defined as

$$r = \frac{\sum_{i \in V} \sum_{j \in N(i)} A_{ij} A_{ji}}{\sum_{i \in V} \sum_{j \in N(i)} A_{ij}} \tag{2}$$

4.2.3. Core-periphery model

The core-periphery model refers to a separation of the nodes in two different sets: the core and the periphery. Nodes in the core are highly interconnected between them, while nodes in the periphery are connected to the core but rarely interact between them. We use the implementation of [Craig and von Peter \(2014\)](#).²

4.2.4. Strength centrality

Strength centrality refers to the sum of its interbank assets and liabilities. Inner strength is the sum of its interbank assets, but the outer strength is the sum of its interbank liabilities. This information is useful to determine which bank is lending (borrowing) the most in the network.

$$C_s(i) = s_i \tag{3}$$

4.2.5. Betweenness centrality

Let $\sigma_{ij} = \sigma_{ji}$ denote the total number of shortest paths between i and j . Let $\sigma_{ij}(v)$ be the total number of shortest paths between i and j that pass through vertex v ; the Betweenness centrality of node v is defined as:

$$C_B(v) = \sum_{i \neq v} \sum_{j \neq v} \frac{\sigma_{ij}(v)}{\sigma_{ij}} \tag{4}$$

4.2.6. SinkRank centrality

SinkRank is a measure based on random walks, and it models the system as an absorbing Markov process in a directed and weighted network. SinkRank is applied in the field of high-value payment systems to identify financial institutions that have a greater power to absorb liquidity from the market in the case of their failures ([Soramaki and Cook, 2013](#)). We follow the same notation as [Soramaki and Cook \(2013\)](#) in what follows.

Networks are represented by their corresponding adjacency matrices, and any such matrices can be transformed into a transition matrix. For a transition matrix associated with a weighted adjacency matrix $W = [w_{ij}]_{n \times n}$, the transition probabilities are given by the link weight w_{ij} divided by the row sum $P = \left[\frac{w_{ij}}{\sum_j w_{ij}} \right]_{n \times n}$. Modelling the payment system as an absorbing system, the transition matrix P can be written as a block matrix in the following way:

$$P = \begin{bmatrix} R & T \\ 0 & I \end{bmatrix} \tag{5}$$

where I is the $m \times m$ identity matrix (m is the number of absorbing states), R is an $(n - m) \times (n - m)$ squared matrix that contains the transition probabilities between non-absorbing states ($n - m$ is the number of non-absorbing states), 0 is a matrix with all entries equal to zero, and T is an $(n - m) \times m$ matrix that contains the probabilities of going from a non-absorbing state to an absorbing state.

The fundamental matrix Q is calculated as $(I - S)^{-1}$, S gives the transition probabilities for movement among the non-absorbing states for an adjacent matrix of payments. Therefore, q_{ij} defines the expected number of transition times between i and j before absorption. The ‘‘Sink Distance’’ of node i is the sum of all the entries in the i th row of Q .

A node’s SinkRank is equal to the inverse of the average Sink Distance from the non-absorbing nodes.

$$SinkRank(v) = \frac{n - m}{\sum_i \sum_j q_{ij}} \tag{6}$$

² We thank the authors for sharing the code to fit their model to the Bolivian payment system network.

4.2.7. DebtRank centrality

DebtRank (Battiston et al., 2012) is a further centrality-based indicator that was introduced to rank financial institutions in terms of their systemic importance in a network of interbank exposures.

If we denote the equity of institution i , by $E_i(0)$ and the exposure of institution i toward institution j , by $W_{ij}(0)$, the algorithm reduces to finding the fixed point of the following recursion Bardoscia et al. (2015)

$$h_i(t) = \min \left\{ 1, \sum_j \left(\frac{W_{ij}(0)}{E_i(0)} h_j(t-1) \right) + h_i(1) \right\}, \tag{7}$$

where $h_i(t)$ represents the relative equity loss of bank i between the iteration t , with $h_i(1)$ representing the exogenous shock that we want to impose on the system.

From the algorithm, it is possible in particular to compute the impact of a bank i , which is defined as the relative loss of equity that the default of bank i would cause to the system (excluding the contribution of bank i , to account only for contagion effects). Similarly, it is possible to estimate the vulnerability of bank i as the average relative equity loss that would be experienced by i because of the initial default of another bank.

4.3. Finding the backbone in financial networks

Given a large complex network, it may be useful to simplify its structure by singling out a subset of “relevant” links, where the notion of relevance depends on deviations with respect to some underlying null model. This can be done in different ways, for example with probabilistic models such as in Carmona and Martinez-Jaramillo (2020). Sophisticated statistical models that take full advantage of the availability of longitudinal network data are the best way to characterize the dynamic behavior of nodes in a network. Nevertheless, a more simple approach, which also delivers good results, is to use filtering methods.

The backbone of the network is obtained by two different filtering techniques that highlight different properties. In this work, we use the Pólya filter (Marcaccioli and Livan, 2019)³ and the Kobayashi-Takaguchi-Barrat (KTB) filter (Kobayashi et al., 2018).

4.3.1. The Pólya Filter

Marcaccioli and Livan (2019) assume that, in a network, each node distributes its weight among its links following a Pólya process with a reinforcement parameter a . The idea at the basis of the method is that the typically observed networks are the aggregate outcome of repeated interactions that occur over time. Furthermore, the presence of a reinforcement mechanism mimics the fact that the more two nodes interact, the more it is likely they will do so in the future. The parameter a can then be used to tune the strength of such an effect.

If we consider a node with degree d and strength s , the null hypothesis at the basis of the Pólya filter is defined as

$$\mathbb{P}(w|d, s, a) = \binom{s}{w} \frac{B\left(\frac{1}{a} + w, \frac{d-1}{a} + s - w\right)}{B\left(\frac{1}{a} + \frac{d-1}{a}\right)}, \tag{8}$$

which defines the probability under the null hypothesis to observe weight w in correspondence to one of the links of the node, and where B denotes the beta function.

4.3.2. The KTB filter

The KTB filter (Kobayashi et al., 2018) assumes that there is no prior knowledge of the characteristics of the network structure, and that there is a permanent probability of interaction between a pair of nodes. The method for the calculation of the backbone is based on undirected edges without weights, given time intervals with binary adjacency matrices A_t with elements $A_{ij,t}$ equal to 1, if there is at least one interaction between i and j and 0 otherwise. Each node i is assigned an activity level variable $a_i \in (0, 1)$ and probability u of interacting with node j . The activity level for a time interval t is given by $u(a_i, a_j) = a_i a_j$. The activity variables rule the probabilities of interactions between nodes and are not directly observable, however they can be estimated using a maximum likelihood estimation. We denote such maximum likely estimation by $a^* \equiv (a_1^*, \dots, a_N^*)$. The calculation of the interaction for each pair of nodes i and j according to the total number of interactions m_{ij} in the null model is performed according to a binomial distribution:

$$g(m_{ij}/a_i^*, a_j^*) = \binom{\tau}{m_{ij}} u(a_i^*, a_j^*)^{m_{ij}} (1 - u(a_i^*, a_j^*))^{\tau - m_{ij}}, \tag{9}$$

where m_{ij}^c denote the c -th percentile of $g(m_{ij}/a_i^*, a_j^*)$ and G the cumulative distribution function. The connection between i and j is a significant tie if $m_{ij}^o > m_{ij}^c$, which means that the empirical number of interactions of the node pairs cannot be explained by the null model at significance level $\alpha \equiv 1 - c/100$.

³ The Pólya urn model is a well-known iterative problem in probability in which, at each step, a two-class element is sampled from the urn and then returned to the urn with an additional element of the same class.

5. Results

In this section, we present the main results of our research. We divide the presentation of the results into two parts. First, we present the structural analysis of the network, the SinkRank centrality metric and the identification of the payment system's backbones. We then present the results for the exposure network, mainly the results of the application of the DebtRank algorithm and its backbone.

5.1. Payments system

The Bolivian high-value payment system has changed over the period analyzed. In particular, we find an increasing number of direct interconnections as a result of a greater number of banks that became part of the LIP system.

In this section, we report a description of the payments network for different time aggregation levels: daily, monthly, yearly, and for the whole period of study. The most adequate time scale aggregation is not determined in this study. Novel statistical models that can assist us in such a decision are currently under development (Carmona and Martinez-Jaramillo, 2020), and this is not the main purpose of this paper. Nevertheless, we report some relevant metrics at different levels of aggregation, as did Kyriakopoulos et al. (2009). However, in one of the applications explored in this work, we resort to a dynamic model, which deals successfully, in our opinion, with some of the issues related to the time scale aggregation problem.

The distribution of the interconnections is not homogeneous, as the majority of links is concentrated on a small percentage of the banks. For the period considered, 5% of participants in the high-value payment system concentrated approximately 60% of the edges. This aspect is linked to the low density of the network, which is small even for the yearly aggregated networks (see Table 4).

According to the reciprocity metric, there is also a considerable chance (always larger than 41%, as shown in Table 4) that interconnections are reciprocated between banks. This aspect could exacerbate the effects of financial contagion. Squartini et al. (2013), for instance, found that the comparison of the reciprocity of an interbank network with that of a suitable null model could provide "early-warning signals" of a crisis.

Table 4
Payments network descriptive statistics

	Daily			Monthly			Yearly		
	Avg	Std Dev	Max	Avg	Std Dev	Max	Avg	Std Dev	Max
Avg (degree)	1.96	0.35	2.97	5.56	1.05	7.29	9.47	1.97	10.97
Max (degree)	20.81	2.95	31.00	41.41	7.35	56.00	57.25	11.73	68.00
Avg (in degree)	1.23	0.23	1.93	4.12	0.73	5.23	7.30	1.50	8.46
Max (in degree)	18.50	2.22	27.00	38.36	8.43	46.00	46.50	3.70	49.00
Avg (out degree)	1.23	0.23	1.93	4.12	0.73	5.23	7.30	1.50	8.46
Max (out degree)	12.88	3.39	27.00	36.36	6.65	53.00	53.75	11.18	65.00
Arcs	122.05	22.88	191.00	408.11	72.62	518.00	723.00	148.50	838.00
Disc. Nodes	66.57	6.89	87.00	36.25	13.61	60.00	22.75	18.01	45.00
Avg (Clust. Coeff.)	0.20	0.04	0.34	0.38	0.09	0.51	0.60	0.10	0.68
Avg (Short. Path)	2.11	0.19	2.62	2.06	0.09	2.23	1.94	0.10	2.07
Completeness Index	1.26%	0.24%	1.97%	4.21%	0.75%	5.34%	7.45%	1.53%	8.64%
LSCC	21.23	3.97	31.00	35.00	9.00	51.00	57.25	15.26	70.00
Reciprocity	40.91%	6.27%	61.48%	65.24%	2.83%	70.74%	70.27%	2.11%	73.05%
Core size	6.27	0.85	9.00	12.41	0.92	14.00	16.50	1.00	17.00
Core Error Sum	32.64	7.71	58.00	50.02	13.78	76.00	68.75	17.69	89.00
Core Std Error	26.99%	5.47%	72.97%	12.05%	1.85%	14.87%	9.46%	0.88%	10.62%

The average clustering coefficient for the monthly aggregated networks is increasing during the period we consider, almost doubling from January 2015 to February 2020. A higher clustering associated with an individual institution denotes a higher density of triangles in its neighborhood, which was interpreted by Silva et al. (2016) in terms of a higher substitutability of the institution. The average clustering coefficient is high, even for the daily networks, as shown in Table 4.

In Figure 5, we show the cumulative degree distribution, the clustering coefficient as a function of degree, and the total strength distribution for different time aggregation levels: daily, monthly, and yearly in the payment network. The degree distribution (Figure 5a) appears to be more heterogeneous with respect to that of Erdős-Rényi random graphs with the same density. Furthermore, the total strength distribution (Figure 6) shows a high degree of heterogeneity among banks, whose strength spans over several orders of magnitude. Heterogeneity in the distribution of degrees and strengths have been associated with higher robustness (with respect to a benchmark of a homogeneous system) of the network with respect to the failure of a random bank, but higher fragility with respect to the failure of a bank with high degree or strength (see, for instance, Caccioli et al. (2012a) in the context of cascades of failures).

In Figure 5b, the clustering coefficients as a function of degree are shown to be a decreasing function of the degree, but to decay more slowly for more aggregated data. This finding is in agreement with Kyriakopoulos et al. (2009).

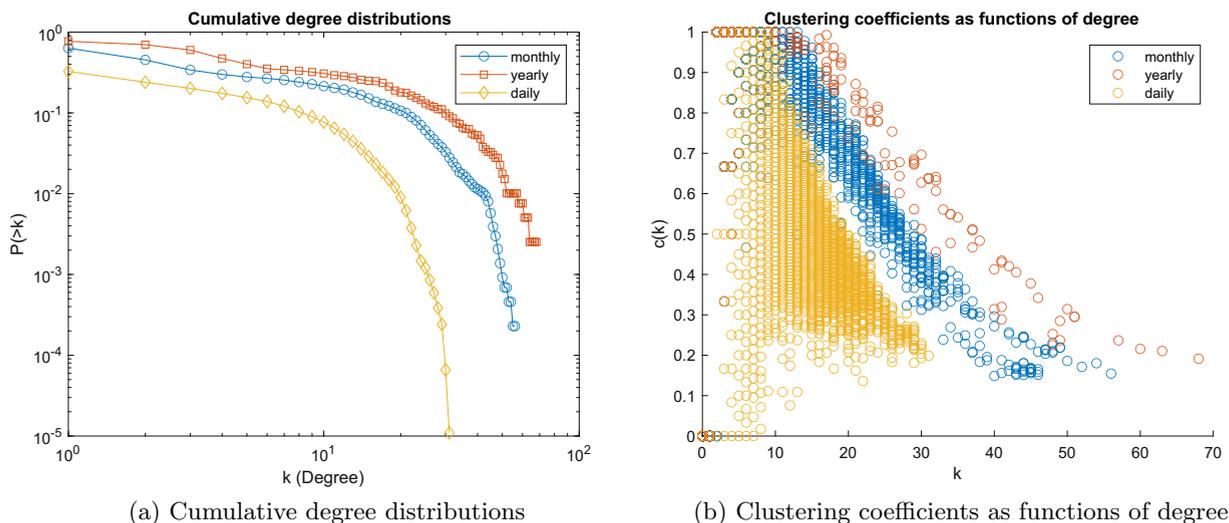


Fig. 5. Distributions of the unweighted payment network

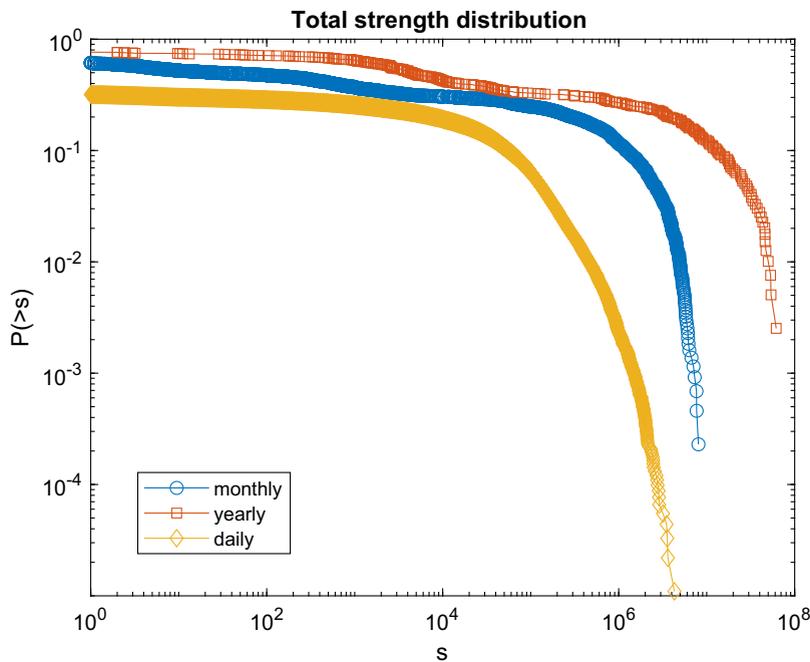


Fig. 6. Total Strength Distribution

In Figure 7, we select the 10 entities with the highest magnitudes of SinkRank. The evolution of SinkRank shows a pattern during the period considered. In particular, the figure shows that two banks reach an important level of interconnection and have a fundamental role for the distribution of liquidity in the high-value payment network. Their eventual exit from the network would cause liquidity contractions that would affect the operation of the network.

To reveal the backbone of the payment system network we used the Pólya and KTB filters for the network built by aggregating all the payments during the period of study (Table 5). The total network reveals that there are no disconnected nodes, high clustering coefficients, or reciprocity, and the network fits relatively well with a core-periphery model. On the other hand, the filtered networks reveal a completely different story: they are extremely sparse networks, with low average degree and low clustering, but high reciprocity. The core size is small, and the fitting to the core-periphery model is poor. Finally, a large number of nodes are disconnected in the filtered networks.

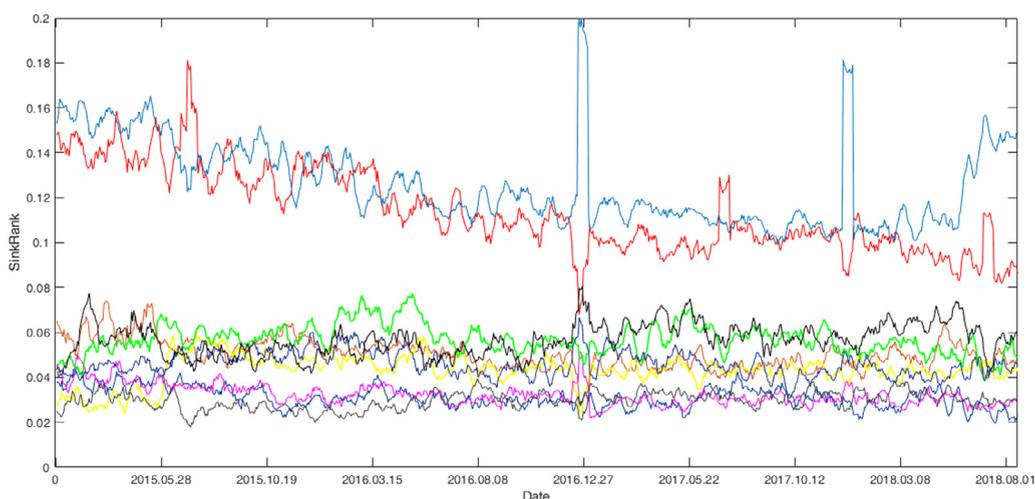


Fig. 7. Bolivian Payments System SinkRank Evolution

Table 5
Statistics for the total payments and the filtered networks

	Total	Filtered	
		KTB	Pólya
Avg (degree)	14.93	2	1
Max (degree)	75	24	21
Avg (in degree)	11.66	1	1
Max (in degree)	55	15	11
Avg (out degree)	11.66	1	1
Max (out degree)	73	15	17
# Arcs	1154	137	79
# Disconnected Nodes	0	49	54
Avg (Clust. Coeff.)	1	0.12	0.08
Avg (Shortest Path)	2	2	3
Completeness Index	11.89%	1.41%	0.81%
LSCC	81	25	21
Reciprocity	72%	42%	53%
Core size	21	6	5
Core Error Sum	109	34	27
Core Std Error	9%	25%	34%

An important result is that the top rankings obtained by the SinkRank centrality metric are different for the different aggregation scales.⁴ This reinforces the view that the determination of systemic relevance for payment systems depends critically on the time aggregation scale used to build the networks. Now, for the filtering algorithms, the top institution is the same, but the rest of the top 10 institutions are different, except one. Therefore, the results are inconclusive, as it is not clear whether the filtered networks can be used for the identification of systemically important institutions.

Nevertheless, we believe that the analysis of the filtered networks is helpful in understanding some structural properties of these systems and their departure from random systems, as we discuss below.

For a randomly selected period, links validated by the Pólya filter (where the reinforcement parameter is determined using maximum likelihood) represent 6 % of total connections and involve 29% of the nodes (Figure 8). The validated links account for 45% of the volume flowing through the network. For the calculation of this filter, the quality of the results depends on the scale aggregation, for this reason we use a monthly scale.

We use the Jaccard index to measure the similarity between two different validated networks (consecutive months). We find approximately 30% of similarity between validated networks in consecutive months (Figure 9, red line); this means that there is some stability among the validated links. On the other hand, we observed about 70% of similarity among the original monthly networks (Figure 9, blue line), which means an even higher persistence for the original links.

⁴ Results are available upon request.

This high persistence of links suggests that it may be important to explicitly account for the temporal structure of relationships when filtering the network. Nevertheless, the Pólya filter is a static model and to the best of our knowledge, there is no a dynamic version of the filter.

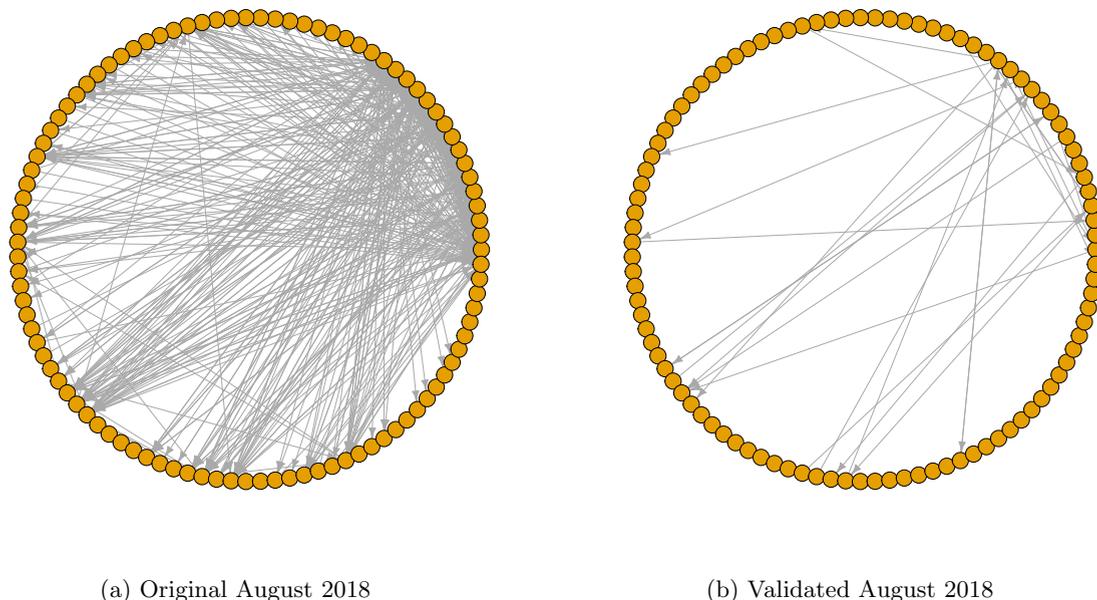


Fig. 8. Monthly Original and Validated Payments Using Pólya Filter

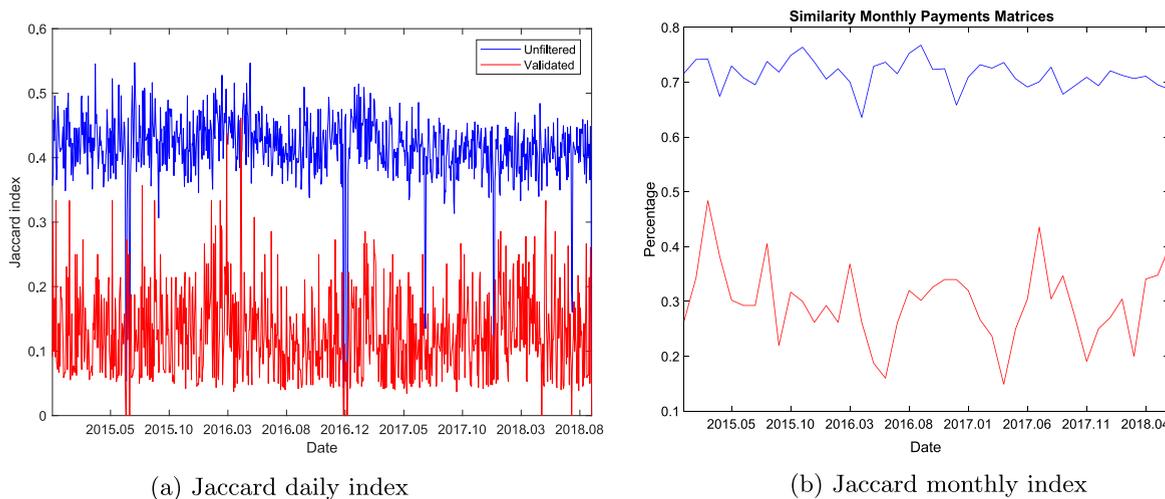


Fig. 9. Jaccard Index Results

To this end, we resort to the KTB filter, which can be used to explain the dynamics of the interaction between nodes in a network with recurring connections. The KTB filter validated 70% of the edges, representing the 15% of the total value of operations, and leaving out 38% of the participants in the original network, which are primarily small financial entities and nonfinancial entities (Figure 10).

The Pólya filter (which accounts for link weights but not for the temporal structure of the network) and the KTB filter (which account for the temporal structure of the network but not for the weights) provide two complementary descriptions of the payment system. On the one hand, the Pólya filter shows that, given a monthly static network, a relatively large percentage of the volume of payments is associated with a small number of validated links. On the other hand, the KTB filter suggests that relatively small links are the most persistent over time. It would be interesting in the future to devise filters that could account for both aspects at the same time.

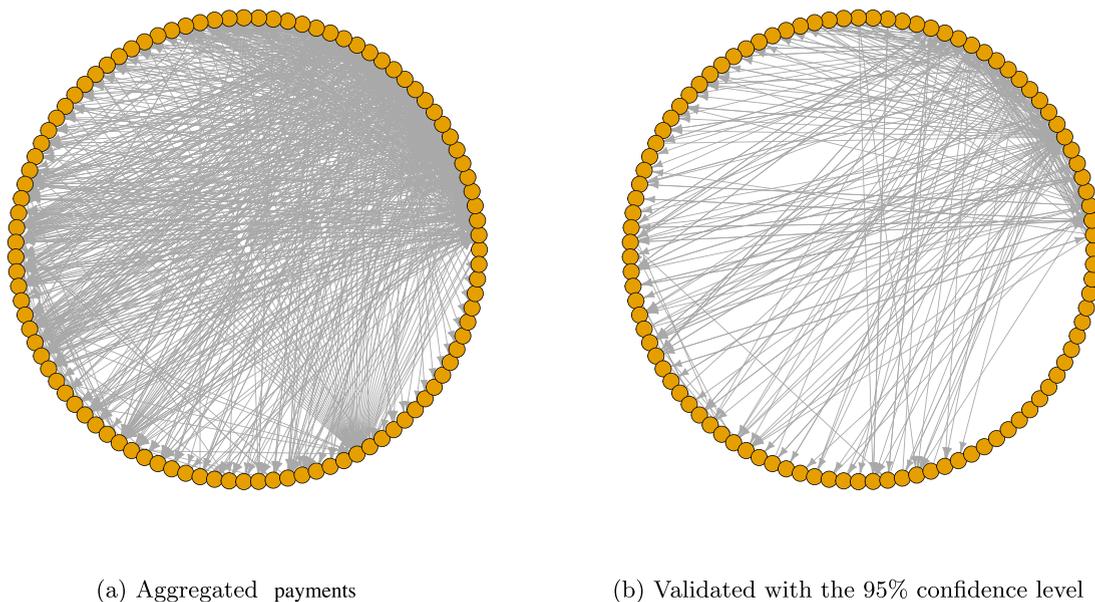


Fig. 10. Kobayashi Approach Original and Validated Payments

The results of both filters are important to approximate the relevance and stability of the connections over time. These aspects would make it possible to specify the analysis on the risks of the high-value payment network based on the critical structures found.

5.2. Interbank exposures

The structural analysis of the interbank exposure networks showed an average completeness index of 0.11 and a 52% concentration of the edges in 21% of the banks, the average strength of the network increases in coherence with the volume of trading in the interbank market (Figure 11).

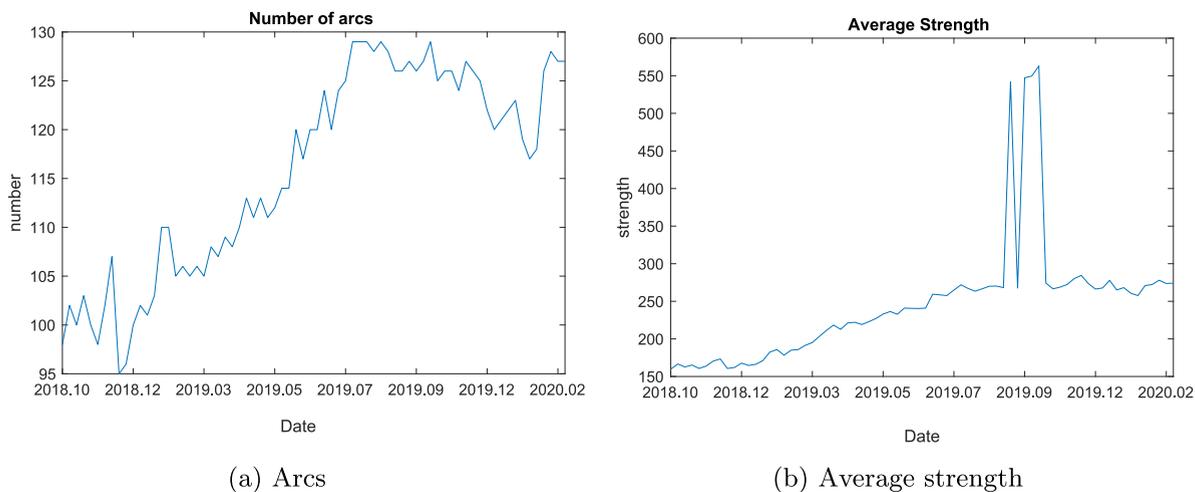


Fig. 11. Bolivian Interbank Exposures Descriptive Metrics

Networks also show an increasing probability of interconnections between banks, which produces an environment of greater interdependencies. The temporal evolution of the network activity metrics (shorter routes and clustering coefficient) are consistent with the behavior of interbank exposures (Figure 12).

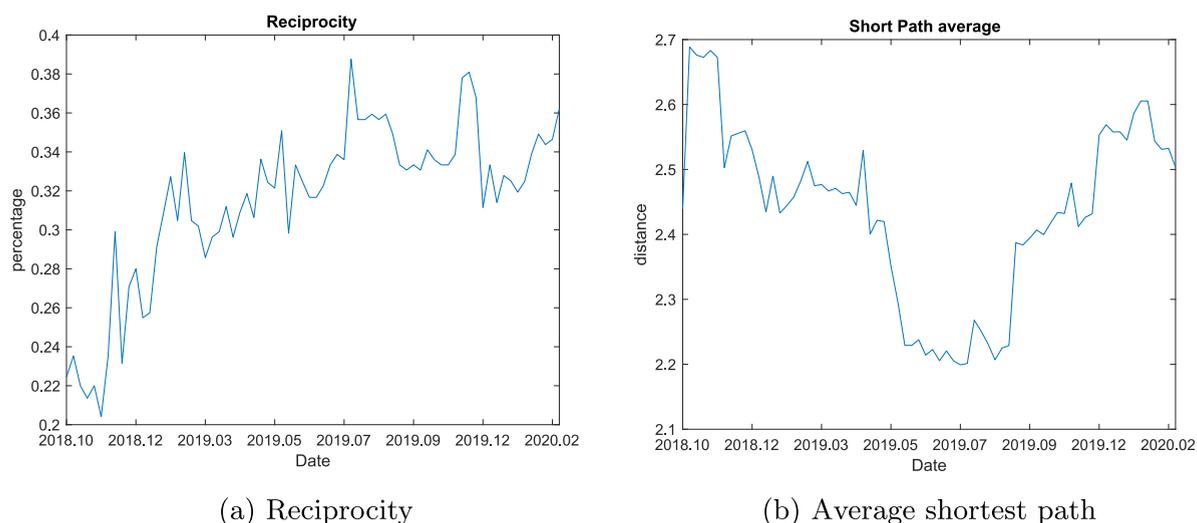


Fig. 12. Bolivian Interbank Exposures Descriptive Metrics

Table 6 shows the basic statistics for the exposures networks, the average network and the filtered ones. First, all the different networks have low density, in particular the Pólya filtered one. The average clustering is relatively high for most networks, again with the exception of the Pólya filtered one. Reciprocity is not as high as for the payment networks, but it is not small. The core size is small, and the fit is very poor. The KTB filtered network preserves many of the features of the weekly exposures, this means that the exposures present a good degree of persistence.

Table 6
Exposures Networks Descriptive Statistics

	Weekly Exposures			Average	Filtered	
	Avg	Std Dev	Max	Exposures	KTB	Pólya
Avg (degree)	4.53	0.32	4.98	7	5	1
Max (degree)	13	0.86	15	18	14	8
Avg (in degree)	2.69	0.24	3.00	4	3	0
Max (in degree)	10	0.90	12	14	12	3
Avg (out degree)	2.69	0.24	3.00	4	3	0
Max (out degree)	12	0.62	13	14	11	7
# Arcs	116	10.46	129	190	126	21
# Disconnected Nodes	7	1.51	9	2	7	27
Avg (Clust. Coeff.)	0.33	0.05	0.43	0.44	0.34	0.05
Avg (Shortest Path)	2	0.14	3	2	3	3
Completeness Index	6.41%	0.58%	7.14%	10.52%	6.98%	1.16%
LSCC	20	1.91	22	23	23	2
Reciprocity	31%	4.17%	39%	51%	32%	29%
Core size	6	0.80	7	9	7	3
Core Error Sum	57	2.65	63	59	57	10
Core Std Error	50%	3.83%	61%	31%	45%	48%

Figure 13 shows the different IDs of financial institutions and their number of occurrences as the core of the interbank exposures. The core is relatively stable over time, with eight entities that are part of the core during the entire period (more than 28 occurrences in the core). Approximately 70% of the entities never appeared in the core of the interbank exposures from October 2018 to February 2020. Only one firm appears in the core for the whole period (72 weeks).

For the measurement and analysis of systemic risk in the interbank exposures market, we compute for each bank its (i) impact, which is the relative loss of TIER 1 capital that would be experienced by the system if the bank were to default, and its (ii) vulnerability, which is its average loss of equity due to financial contagion after the initial default of another bank.

The results show that the impact and vulnerability register a positive trend in the period we consider. A significant growth in impact and vulnerability is observed during the 37th, 39th, 40th, and 41st weeks of 2019 due to abrupt increases in the volume of interbank credits.

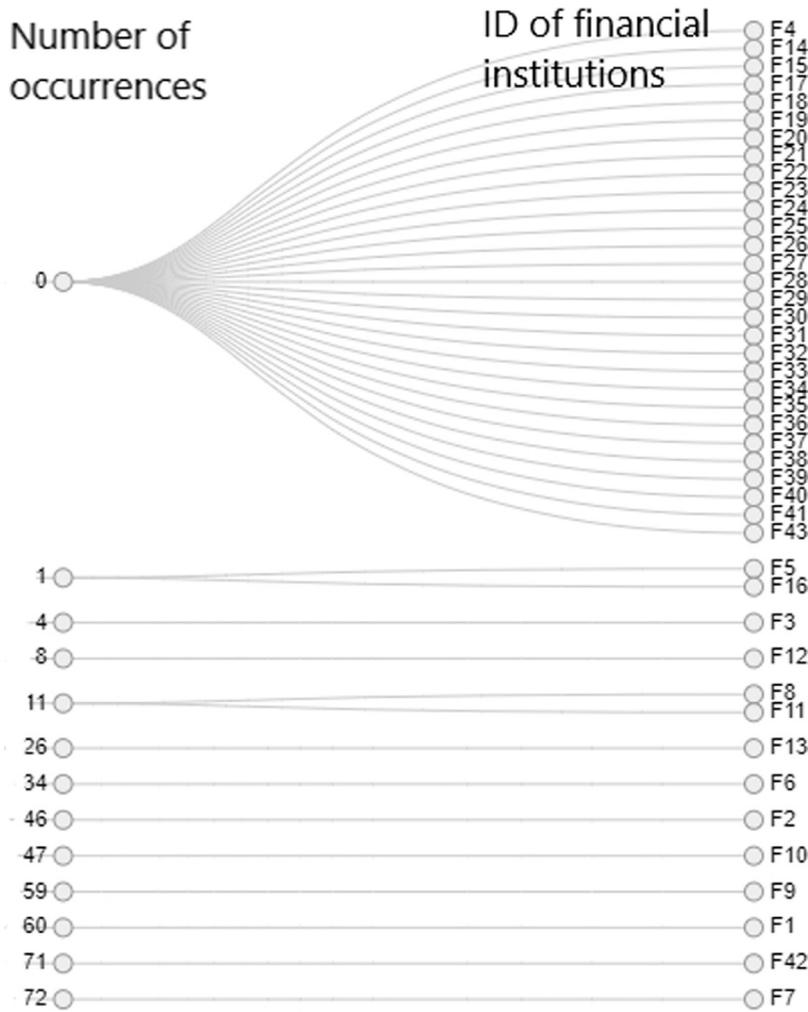
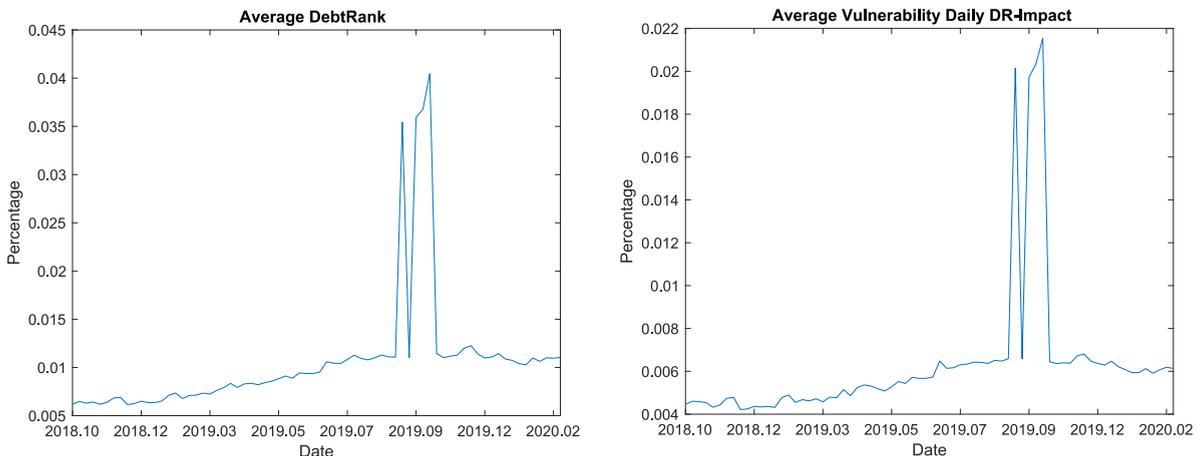


Fig. 13. Alluvial Graph

The sudden increases in DebtRank and vulnerability are explained by political and social events that occurred in Bolivia to cause an environment of uncertainty among the population, which negatively affected expectations regarding financial conditions and produced massive withdrawals of bank deposits (Figure 14).



(a) Average DebtRank

(b) Average Vulnerability Weekly DR-Impact

Fig. 14. Systemic Risk Results

Impact and vulnerability register a slight increase in the scenario, with Tier 1 adjusted for unexpected losses (see Figure 15, the latent exposure to a firm’s credit risk has a marginal impact on the solvency of banks).

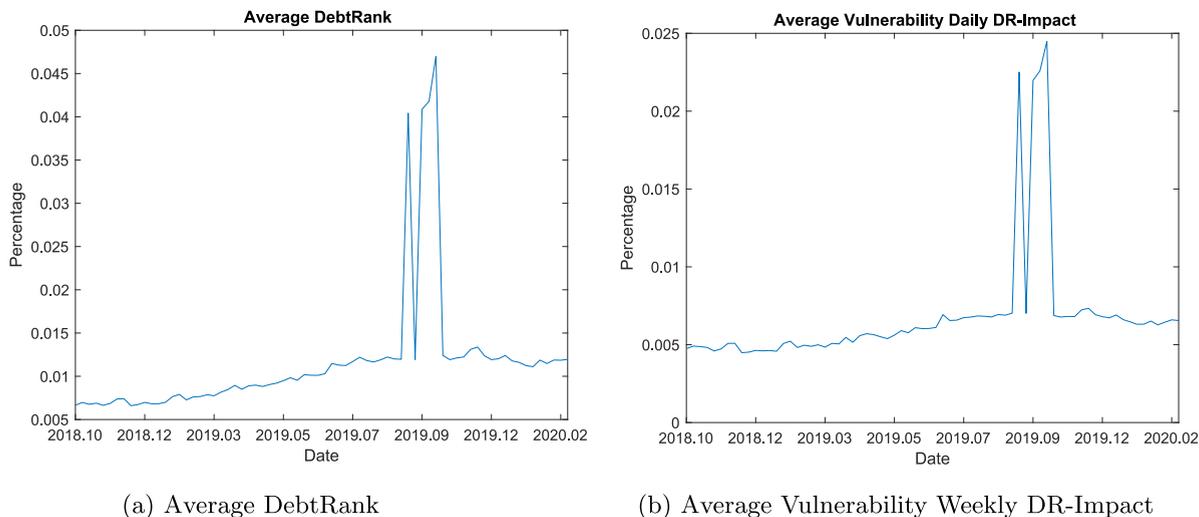


Fig. 15. Systemic Risk Results Adjusted by Losses

Figure 16 shows two phases of the systemic risk of the network of interbank exposures. Panel (a) shows the situation two weeks before DebtRank reached its maximum level. Panel (b) shows that, because of a general exacerbation of systemic risk, banks register drastic change in relation to their initial impacts and exposure positions. Banks that simultaneously concentrate high levels of exposure and impact are especially relevant in the system because their greater vulnerability is also linked to the occurrence of a far-reaching financial contagion.

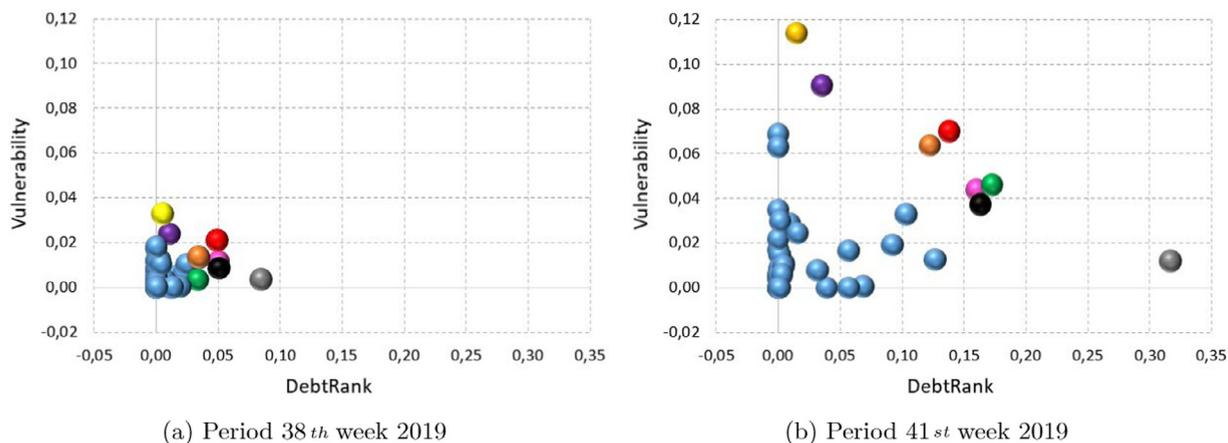


Fig. 16. DebtRank and Vulnerabilities

As a stress-testing exercise, we calculate the maximum value and the 90th and 95th percentiles of DebtRank. This exercise allows for observing the maximum levels of Tier 1 losses, which reach 0.32 in the case of Tier 1 without loss adjustment and 0.36 with Tier 1 adjusted for losses. It also shows a high dependency in a small number of banks because there is an important difference between the DebtRank average and the magnitudes estimated in stress-testing. The conditions considered for the test evidence a high robustness of the interbank exposures network (Figure 17).

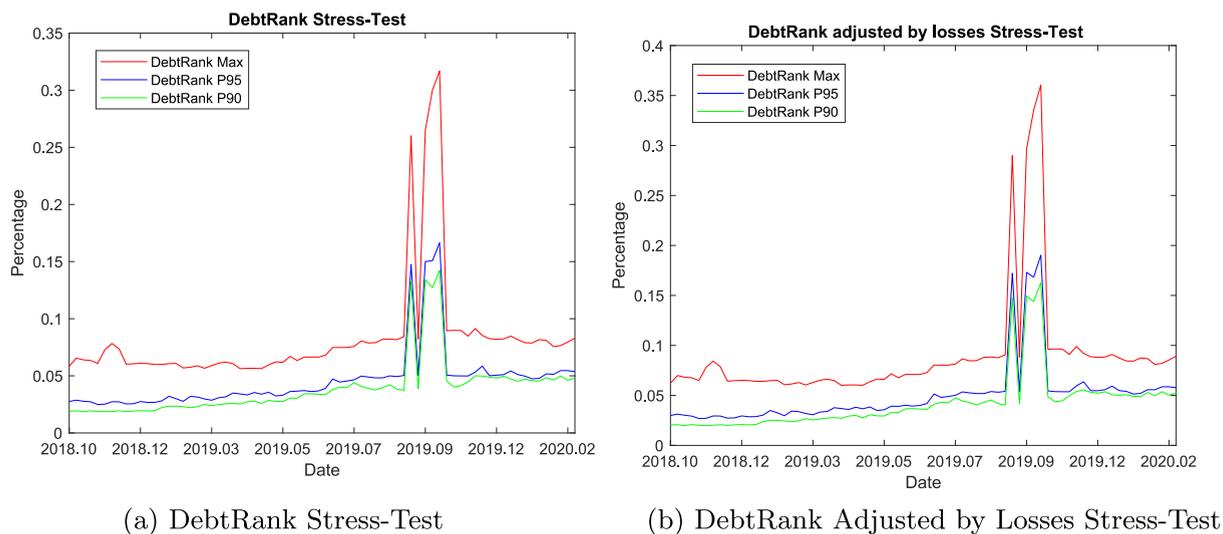


Fig. 17. DebtRank Stress testing

Figure 18 shows the change that banks register in terms of financial impact and vulnerability for each entity for weeks of relative stability and tension. It is possible to observe a widespread change in the risk profiles of banks, which translates into exacerbation of systemic risk.

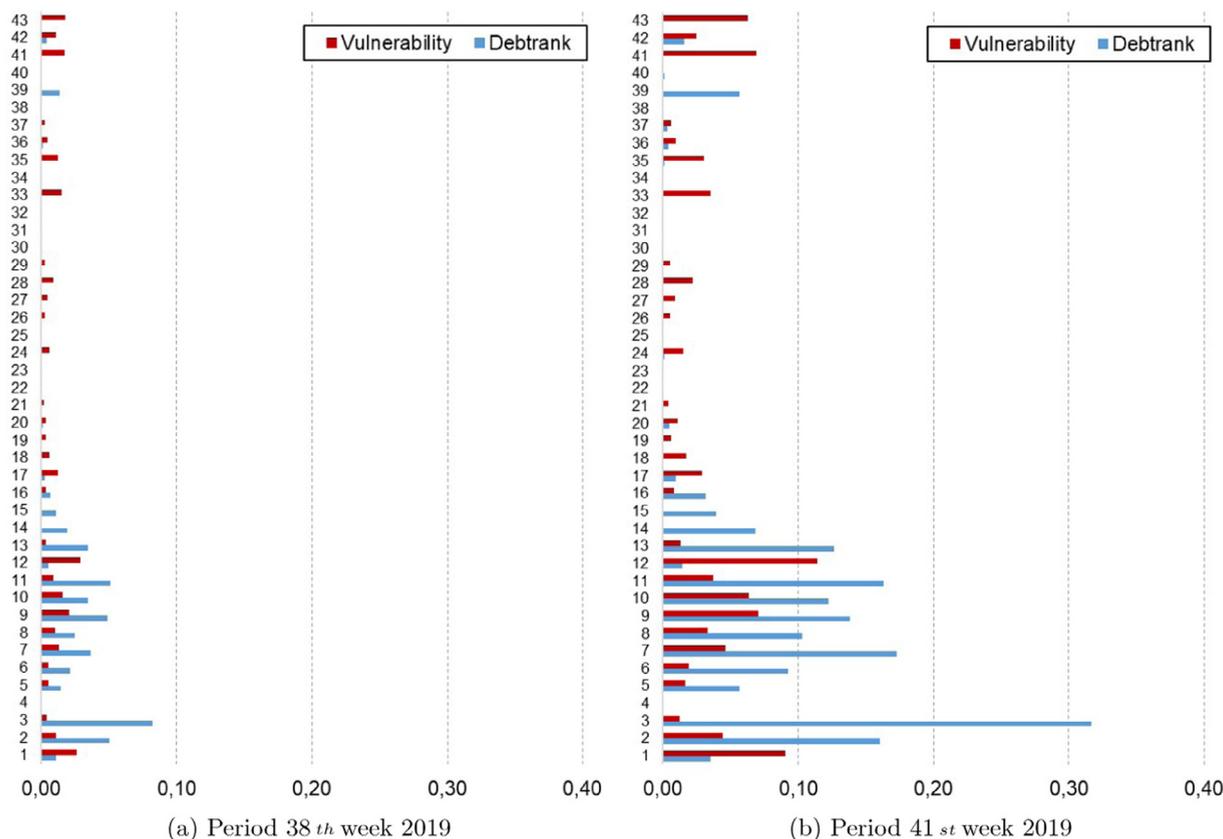


Fig. 18. DebtRank and Vulnerabilities Profiles

The backbone estimated with the KTB filter for interbank exposures shows the links with the greatest persistence over time. With this filter, a relatively high proportion of links are validated, in contrast with the payment system network. This situation highlights the preference. Furthermore, confidence-based relationships are very important in the unsecured interbank market (Figure 19b).

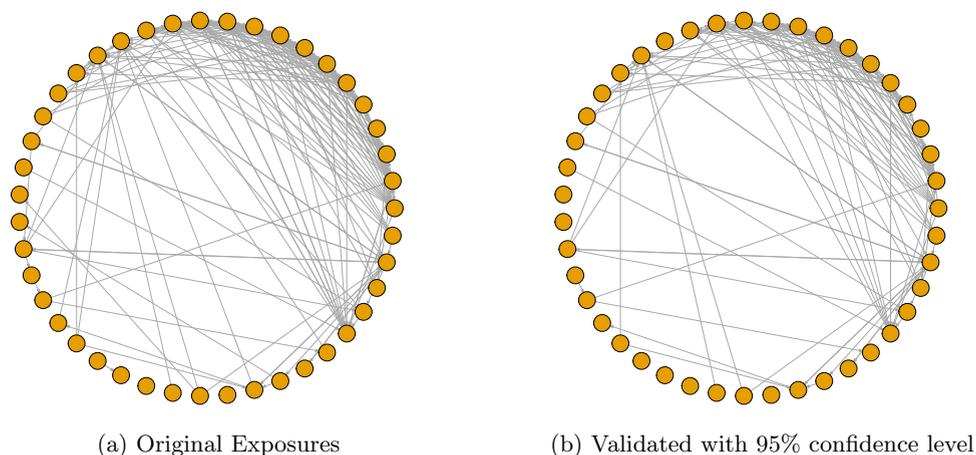


Fig. 19. Original and Validated Exposures using KTB Methodology

6. Conclusions and further work

The main contribution of this work consists of studying two important sources of interconnectedness in the Bolivian banking system: the payment and the interbank exposures underlying networks. These two layers of interaction among financial institutions constitute two important sources of connectivity in the financial system. The most important conclusions of these two studies are the following:

- The analysis of the payment system reveals that different time scale aggregation of the payment system activity leads to a different structural description of the system, which then reflects in different rankings of systemically important institutions as measured by SinkRank.
- The exposure network shows increasing reciprocity, number of arcs and average strength over time. This is associated with a corresponding increase of impact and vulnerability of the institutions.
- As measured by DebtRank, systemic risk in the Bolivian financial system has increased slightly in the last two years. Furthermore, the DebtRank algorithm revealed a short period in which systemic risk doubled in the Bolivian banking system. This short-lived episode is linked to a period of political instability that produced a situation of financial instability. The sequence observed was as follows: the political situation caused an environment of social uncertainty that resulted in massive withdrawals of bank deposits and illiquidity conditions for banks, therefore interbank operations and exposures increased considerably.

Despite the encouraging initial results on the contagion study, it is still necessary to complete the systemic risk analysis by including more types of direct and indirect exposures. This will lead to a more comprehensive estimation of systemic risk in the Bolivian banking system. In the case of the payment system, once the structural study has been performed including the identification of the system's backbone, some of these metrics can be used for other purposes, such as the identification of anomalous payments or changes in the behavior of the participants.

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