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Risk monitoring in Ecuador's payment system: Implementation of a network topology study ☆

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A B S T R A C T

Payment systems are fundamental pillars of countries' economic stability and financial systems. Central banks use them to promote safe and efficient electronic payments. As such, central banks have developed various tools to control and monitor inherent risks such as systemic risk, liquidity risks or operational risks that could affect one or more members of the system, and thus affect the payment chain of a given country.

Our objective is to present a network topology methodology as a tool to study the characteristics and properties of the Interbank Payment System (SPI) in Ecuador. We establish systemically important players to determine whether their absence in simulated scenarios would cause financial contagion to the rest of the participants in the SPI. We have applied our network topology tool to detect systemic risk in the SPI during the period of the SARS-COV-2 pandemic in 2020. We found that the SPI payment network is sensitive to the absence of its systemically important participants, as well as to exogenous events such as the pandemic, due to which a loss of network stability (payment execution delinquency) arises.

This paper constitutes a first application of the network topology for the Ecuadorian case, and at the same time a tool for preventive or corrective policymaking on disruptions in the SPI payment system.

1. Introduction

Efficient payment systems stimulate a country's economic performance (Bech and Garratt, 2003), so their security and efficiency should be public policy objectives: due to a lack of incoming funds with which to finance outgoing payments, potential illiquidity would lead to illiquidity in the payment system. In other words, coordination and synchronization among financial institutions is required to ensure they have the necessary liquidity and execute their payments on time.

Therefore, the authority in charge of the payment system must identify, monitor, manage, measure and control risks in the payment systems to make them safe and efficient. In this sense, network topology (NT) methodology has been used as an instrument to analyze the structure and operation of payment networks, which unify and involve financial entities through the transactions executed among them (Borges, Ulica and Gubareva, 2020).

However, the use of NT for payment systems occurs because it provides information about the interconnectivity or dependent relationships between participants (Sahabat, Silalahi, Indrastuti, & Herlina, 2020), revealing who dominates a network in terms of connectivity and amount of payments (i.e., who is systemically important; Rohrer, Malliaris, & Tschorsch, 2019)—a quality of certain

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financial institutions that makes payment networks heterogeneous and sensitive to financial contagion (Borges, Ulica and Gubareva, 2020), just as happened during the financial crisis of 2008 (Alamsyah and Ramadhani, 2018).

The literature on systemic risk in payment systems with NT starts by identifying the structure of a payment network via its network centrality indicators and participants to determine their distribution in terms of connectivity and learn who dominates the network. Then, researchers simulate whether to exclude dominant players from the payment network causes financial contagion among the rest of its members. We apply the same process to the Ecuadorian Interbank Payment System (SPI). However, we examine the heterogeneity of financial institutions in greater depth using a clustering analysis. We contribute to the literature on NT in payment systems by considering several indicators of centrality, not just a few such as coefficient betweenness, closeness or page rank. In other words, we offer robust diagnosis of which financial institutions are systemically important (i.e., their absence and illiquidity when making payments would mean the beginning of financial contagion). Based on our data, policymakers can know which entities to safeguard against events of illiquidity in or disconnection from the payment system.

However, our major contribution will be to the national literature, as to date, there has been no similar study in Ecuador. Therefore, ours is a case study, as we apply a widely used tool to the Ecuadorian context by analyzing the NT and stability of Ecuador's SPI under normal and stressed conditions. This paper aims at constructing, visualizing and examining the transfer networks compensated by the SPI. The results are useful to better understand how NT and stability work, since the SPI is the financial infrastructure that clears and settles the greatest amount and value of wire transfers by natural and legal persons in Ecuador.

Based on our results, it is possible to suggest a series of policies aimed at guaranteeing the normal flow of payments, whether through preventive actions that reduce the probability of system interruptions or remedies that allow prompt recovery of network stability.

We review the literature in the following section. In the third section, we describe the SPI and its generated payment network. A fourth section shows the NT results for the SPI as well as applying a simulation to evaluate Ecuadorian national network stability in a scenario of non-participation of systemically important financial institutions. To understand similar behavior among network entities, we complement this information with an analysis of the data clusters. In addition, we observe the behavior of the SPI payment network in the case of the economic shock at the beginning of the COVID-19 quarantine. Finally, we present our conclusions.

1.1. *Interbank payment system*

According to Ecuadorian regulation, the Central Bank of Ecuador must provide the physical and electronic means of payment necessary for the proper functioning of the country's economy. In this context, the central bank is the administrator and operator of several payment systems, which are known as the Central Payment System (SCP). The SCP includes the interbank fund transfer system for high-value payments and supports the settlement of private retail payment systems as well as securities clearing and settlement systems. Thus, the SCP represents the most relevant payment infrastructure for Ecuador. The underlying system that makes up the SCP is the SPI. The SPI liquidates approximately 66% of all payments in the SCP; this system is considered systemically important in Ecuador because it is the only payment system in the country. Therefore, if it were to fail, so would the payment chain, as there is no substitute to take over the functions of the SPI. In other words, the liquidity of the economy through payment relationships is very sensitive to interruptions of the systemically important SPI. Because of its importance, our work focuses on SPI activity.

Since the implementation of the SPI in 2002, the total amount and number of transactions settled in this system has grown year after year. In 2019, the SPI settled more than USD 113 billion with a corresponding number of transactions of nearly 75 million, representing a daily average of USD 472 million and 314 thousand transactions. The private sector channels USD 76 billion via 33 million transactions, and the public sector USD 37 billion via 41 million transactions. As for the clearing and settlement mechanism, the SPI performs payment settlement at three daily time intervals. Each time interval represents an intraday settlement period for interbank payments ordered by financial institutions in the SPI. These time intervals are scheduled at three different times: 08:30, 11:00, and 16:30. Each time interval excludes the others. The net amounts among financial institutions are cleared and settled at the end of each time interval.

To do this, the SPI uses transaction information from the 55 largest financial institutions in the country (24 private banks and 31 savings and credit cooperatives) that are SPI participants, representing about 94% of the amount channeled by the private sector. The payment network consists of transactions that are channeled together and form a maximum number of connections equal to 2,970; however, it must be considered that participants have different levels of activity within the network: some financial institutions with greater connectivity make payments with all other SPI participants, but other SPI participants only transact with a few entities in the payment network.

The 55 participants channel USD 71 billion per 32 thousand operations via the SPI, and the five participants who channel the greatest amount represent 78% of the amount analyzed and 73% of all operations. In the case of a complete payment network (connection between all participating financial institutions), 3,025 connections would be expected; however, on the days of highest channelized amounts in the SPI in 2019, there were 1,059 connections, representing only 35% of maximum connectivity. On the day of the greatest number of operations, there were 1,271 connections (42% of the expected amount). The day with the fewest operations reached 908 connections (30% of the expected amount). In all these events, 53 financial institutions participated. The level of connectivity among participants reflects the importance of monitoring network stability, as some financial institutions could impact systemic risk or cause financial contagion due to the concentration of large amounts of funds in only a few financial institutions.

The maximum number of flows a financial institution can have in the system is 54, reflecting that it can send payments to all 55 participants minus itself. Thus, participants with 54 links are the most connected in the network, maintaining payment relationships with all other nodes. This fact positions them as the most influential in the network—other, less connected financial institutions are linked to most nodes through them.

Therefore, developing an automated monitoring tool to identify the behavior of the payment network and analyze risks to financial stability can enable timely identification and measurement of potential impacts while facilitating communication and coordination among participants involved in preserving that stability. Such a tool could alert policymakers of potential systemic risks arising from financial contagion as identified through the payment network.

2. Related literature

The usefulness of NT for analyzing the behavior of payment systems in the case of liquidity stress has been demonstrated in studies of several countries, most of them seeking to characterize their payment networks and monitor their stability. The literature we analyzed recommends using NT to create interrelated representations of participants in a payment or financial system. This method can diagnose baseline indicators of network behavior, identify the most systemically important participants, and thus avoid potential financial contagion that could impact a country's economic activity.

Among the pioneering documents are Soramaki et al. (2006) and Bech and Garrat (2006), who used NT to characterize the United States payment system (Fedwire). Inaoka et al. (2004) applied these principles to the Japanese payment system (BoJ-Net), Becher et al. (2008) in the United Kingdom, and Pröpper et al. (2008) in the Netherlands.

Inaoka et al. (2004) applied the NT technique to Japan's payment system (BOJ-Net), reporting 546 participating financial institutions during June 2001–December 2002. Their results suggest that entities with the greatest connectivity are the most likely to generate financial contagion, and that their inactivity generates havoc in amount of operations, number of operations, and network connection stability.

Soramaki et al. (2006) examined the Fedwire payment network, characterizing it as a co-centralized, small-world network; i.e., the commercial banks that are part of it transact payments quickly. This behavior was exhibited during the period of analysis except for certain holidays. Soramaki et al. (2006) analyzed the impact on the payment network due to the events of September 11, 2001, as well. They determined that the few commercial banks that participated made few payments; i.e., the efficiency and stability of Fedwire decreased as connectivity decreased and the minimum distance (average of transactions between commercial banks) increased.

Becher et al. (2008) studied the UK Clearing House Automated Payment System (CHAPS) between July 2005 and July 2006. CHAPS consists of 15 banks. Under an NT approach, and due to their transactional relationships, the CHAPS network is well connected. This does not vary much daily, and the network is quite resistant to shocks after tests performed by eliminating banks. This study only identified indicators of aggregate network behavior and not nodes, so it could not determine systemically important participants.

Pröpper et al. (2008) applied NT theory to the Dutch payment system, finding that the payment network was small (on real nodes and links), compact (in route length and eccentricity) and scarce (in connectivity) for all periods of time. Relationships on the Dutch network tended to be reciprocal and were on average just 2 steps away. In addition, Pröpper et al. (2008) assessed the long-term systemic stability of the network. Assessing their built network, they identified that it has not substantially affected the structure and stability of the network.

In Central America, fewer published studies analyze NT applications in the payment system field. These include studies for payment systems in Colombia, Mexico, Bolivia, and Jamaica.

As for example the work done for Cepeda (2008) on NT in the high value payment system (CUD) of Colombia. The authors analyze transfers of funds as value networks are exposed to financial risks and focuses on networks' structure, functioning, and stability. They also quantify the impact of simulated shocks on stability and settled value in the network by excluding the five most connected and channeled entities. Complementary, Machado et al. (2010) also assessed the resilience of the CUD when a systemically important entity does not participate. For this, Machado et al. (2010) Used NT to identify whether the CUD payment network was robust, stable, and concentrated. They did so by simulating the iterative exclusion of the most connected (systemically important) institutions on days of higher and lower channelized amounts. Then, they also excluded the institution with the greatest number of operations. Machado et al. (2010) concluded that the network suffered impacts in amount and transactions of up to 9.1% and 7.4%, respectively. In addition to marginal losses of stability (measured in diameter and average distance), other financial institutions are left out when the most connected ones are excluded. León & Murcia (2012) built an indicator using principal component analysis containing centrality indicators obtained via NT methodology, obligations, and immediate liquidity of the participants in the CUD to identify systemically important entities. Ortega & León (2018) sought to characterize Colombia's ACH low-value transfer system, for which they also used an NT tool with information from January 2014 to December 2015. They determined that it is a dense, homogeneous network with concentrated but heterogeneous connectivity with respect to the transferred values.

In the case of Bolivia, Santos & Inchauste (2013) used a "too interconnected to fail" approach to present a new tool to analyze systemic risk in Bolivia's High-Value Payment System (SIVO). Santos & Inchauste (2013) applied NT models and simulations to study the characteristics of network structures, to establish systemically important actors through quantitative criteria, and to estimate the magnitude and extent of direct financial contagion that could occur in the wake of a crisis. SIVO is a non-homogeneous payment network, so it has central and peripheral participants. The results at three different junctures for the Bolivian case during the period 2007–2010 show that direct financial contagion would not have compromised financial stability (Santos & Inchauste, 2013). The centrality betweenness, closeness centrality, degree of centrality, hub, page rank, and centrality authority metrics made it possible to identify systemically important institutions.

Martinez-Jaramillo et al. (2014) evaluated Mexico's SPEI payment system from January 3, 2005, to December 31, 2010, using an NT tool with information on payment transactions among commercial banks. The authors emphasized that systemically important institutions (those with the greatest connectivity) are not strictly the financial institutions with the greatest asset value. This result was obtained by constructing an indicator of general centrality based on principal component analysis of metrics: betweenness centrality, closeness centrality, eigenvector centrality, page rank, and degree of centrality.

In Jamaica, (Marshall, 2017) sought to determine the behavior and resilience of Jamaica's payment system (JamClear-RTGS), for which the author used NT as a method of system description, measuring betweenness centrality, closeness centrality, eigenvector centrality, and degree of centrality. The JamClear-RTGS payment network was examined at two times, January 2–31 and December 1–31, 2015, as these were periods of low and high liquidity in the payment system. Marshall (2017) identified the banks with the greatest connectivity as systemically important. Subsequently, he performed a simulation excluding these entities in a hierarchical manner, resulting in a resilient and stable payment system: although the amount channeled decreased, participants who were not excluded continued exchanging payments.

NT methodology is more commonly applied to financial networks to systemically identify entities. In this sense, Gong et al. (2019) reconstructed the relationships between commercial banks, securities houses, and insurance companies for the Chinese financial system using causal relationships in Granger's sense of expected returns. Gong et al. (2019) analyzed a 24-node network under the metrics of closeness centrality, eigenvector clustering, and degree of centrality, allowing them to identify the most important actors according to their connectivity and by classifying the most important nodes that could cause financial contagion. For the latter, they created a systemic risk indicator using primary component analysis and centrality metrics. Markose et al. (2012) also studied a financial network based on the U.S. credit market in the 2007 and 2008 trimesters using the information on each institution's balance sheets. Their results suggested that just a few institutions concentrated the credit network, and because it was concentrated and dense, the spread of defaults in the housing market was rapid. In addition, in identifying systematically important institutions and spreading contagion, Kusubas et al. (2014) analyzed the money market (credits and deposits) in Turkey between January 11 and December 21, 2000. The network of 83 participating entities was highly connected on average, but not reciprocal. It also met the concentration of connectivity in a handful of participants, making them the most important, whose failure would significantly damage the Turkish payment system.

From this background, the literature agrees that NT is a tool to monitor central banks. NT allows to the public regulators to monitor financial stability and identify deficiencies in the design and performance of the payment system infrastructure. Poor infrastructure can increase the likelihood of systemic risk, with significant deterioration in network stability and reduction of the converted value in a payment network.

In addition, we observed that the articles reviewed all determined which nodes (financial entities) were systemically important, since they connect to such an extent that other scarcely connected entities need the well-connected ones to become much more closely linked in the payment network. This reveals a heterogeneity in networks that makes them sensitive if a financial entity with greater connectivity ceases to participate. Nonparticipation could create a risk of contagion, leaving the other entities that need to transact payments without participation. However, it is possible to determine the amount of risk via NT indicators, as they indicate which entities are the best connected and therefore the most systemically important.

Therefore, we will take the same path that marks the literature on the application of NT—determining systemically important financial institutions and the fragility of the SPI payment network in Ecuador. A study of this type is still absent; that is, we do not know how sensitive the SPI payment system is, nor which financial institutions are most likely to generate financial contagion. Both topics are characteristics of payment networks, including Ecuador's.

3. Methodology

NT was used to estimate, study, and understand the main properties of the SPI network. Indicators were also obtained to identify systemically important participants within the network. We simulated specific events to assess the methodology, which could impact network stability. In addition, to learn common behaviors among heterogeneous financial institutions, we applied a non-hierarchical *k*-medoid classification method. *k*-medoids allowed us to identify and analyze communities or groups of similar financial institutions.

3.1. Network topology

NT can be defined as a physical map in which a network is a set of nodes (vertices) interconnected through links. Jungnickel (2013) and Schröder (2018) point out that a graph G is made up of two sets V *and* E, where $V \neq \emptyset$ and its elements are called vertices or nodes. Set E contains all the links or edges between two vertices $v \in V$. So, $e = \{i, j\}$ indicates that there is a link, edge, or connection between vertex i and vertex j. Graph G can be represented in terms of V *and* E; that is, $G = \{V, E\}$.

Although a graph can be represented using a set of vertices and links, this can become cumbersome. For instance, a graph G can exist such that the set of vertices $V = \{1, ..., N\}$ and the possible connections are $E = \{(1,1); (1,2); (1,3); ...; (N, N)\}$. That is, each of the N vertices can have a connection with all the others. In cases like these or in simpler ones, the representation of graph G is made with adjacency matrix A. Adjacency matrix A is an $n \times n$ matrix in which the nodes are represented in rows and columns. So, an element $a_{ij} = 1$ represents a link between nodes i and j. Conversely, if $a_{ij} = 0$, there is no connection between these vertices. The adjacency matrix can be directed or undirected, in which cases it will be symmetric and non-symmetric, respectively.

If graph $G = \{V, E\}$, has a set of vertices $V = \{1, 2, 3, 4, 5\}$ and a set of bonds $E = \{(1, 2); (1, 3); (1, 4); (2, 4); (3, 5); (4, 5); (5, 1); (5, 2)\}$, the directed ($A_D$) and undirected ($A_{ND}$) adjacency matrices are:

$$A_{Directed} = \begin{pmatrix} 0 & 1 & 1 & 1 & 0 \\ 0 & 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 0 & 1 \\ 0 & 0 & 0 & 0 & 1 \\ 1 & 1 & 0 & 0 & 0 \end{pmatrix} A_{Undirected} = \begin{pmatrix} 0 & 1 & 1 & 1 & 0 \\ 1 & 0 & 0 & 1 & 1 \\ 1 & 0 & 0 & 0 & 1 \\ 1 & 1 & 0 & 0 & 1 \\ 1 & 1 & 1 & 1 & 0 \end{pmatrix}$$

An undirected adjacency matrix implies that the links are not addressed; that is, it does not consider which node one leaves and which one arrives at. An adjacency matrix does describe this. An undirected adjacency matrix has links without orientation and directed adjacency matrices do take orientation into account. However, in this work we considered the orientation and weighting of the links between nodes as suggested by the literature. The nodes of our network are the financial institutions and the connections between them are the links, whose weighting is equal to the payments made. In other words, we created an oriented and weighted network. Operations carried out with the Central Bank of Ecuador and between the same participants were excluded.

Based on the above, it is possible to determine structural indicators of a network to identify its behavior, but it is also possible to determine the indicators of centrality by financial institution. This process reveals which network participants are the most systemically important.

3.1.1. Structural indicators of the network

i) **Density**

Density is the ratio of the number of existing connections versus the maximum number of connections. Its scale ranges from 0 to 1. Values closer to 1 means that a network is complete, as it has all possible connections; values closer to 0 indicate that network connections are scarce.

i) **Minimum distance**

Minimum distance is the average number of links needed to connect between the nodes of a network. The minimum value can be 1, implying that a network has high density. If the network is sparse, the minimum distance will increase.

i) **Diameter**

Diameter is the maximum number of links that the nodes of a network need to connect. A diameter equal to 1 would indicate that the nodes have direct connections.

i) **Transitivity to clustering coefficient**

This coefficient measures the proportion that two nodes j and k, which are not directly connected, have. they are each linked to a node i, so that they can form a triangularization through node i, and nodes i and k can already be connected. The total number of triangulations through a node i with respect to the total number of triangulations in the network form the proportion of the clustering coefficient. Where higher ratio values indicate that multiple clusters of three are formed between nodes in a network and that the network is concentrated.

i) **Reciprocity**

Reciprocity is the proportion of bilateral connections between two nodes i and j versus the maximum number of connections in the network. The higher the reciprocity ratio, the denser the network is said to be, i.e., the more connections there are.

Obtaining and analyzing structural network indicators is possible because the database is in an unstructured format; i.e., variables and observation units are found in the rows. Thus, each financial entity appears as the issuer of a payment (node i) to other financial entities that will receive it (node j), establishing relationships between them (links). In this way, it can be known how many connections exist (real relationships between nodes i and j) compared to the ideal total when all entities are related (density). We can also determine the minimum (minimum distance) and maximum numbers of links (distance) needed to make payments.

Determining the structural indicators of a network helps to know whether its participants have a fast connection (minimum distance) and how long payment could take (diameter). Likewise, we will know the proportion to which network connectivity (density) is reciprocal, but also whether the network is linked to a concentration (clustering coefficient), which describes the existence of certain nodes with much more connectivity than the rest. However, all this is known in a general way, as a characterization of the network. To know in depth, we must resort to the following indicators of centrality by financial institution based on Jungnickel (2013), Schroder (2018), Ortega y León (2018), Cáceres y Aldazosa (2012), and Cepeda (2008).

3.1.2. Nodal centrality indicators

i) **Grade**

A node's grade is the number of links it has to all other nodes. The higher the value, the more connected a node is in the network.

i) **Intermediation or Betweenness centrality**

This is the number of times a node functions as an intermediary (like a bridge) connecting two other nodes that do not have a direct connection. This indicator allows us to find the most important nodes of a network, through which the network maintains its density.

i) **Closeness centrality**

Closeness centrality reflects the distance from a node to the rest. The more connected a given node is, the lower its value will be. Therefore, this metric also indicates the most influential nodes in the network.

i) **Authority**

Authority describes a node's level of importance between 0 and 1. Nodes with a value equal to 1 or very close to it are the most connected in the network; i.e., they are the most important.

i) **Eccentricity**

Eccentricity is the maximum number of connections from a node to the least connected node in the network. The greater the connectivity of each node, the lesser the eccentricity value.

The underlying idea of centrality indicators is to determine which nodes are the most influential, the most systemically important in the network. If this connectivity is concentrated in a reduced number of nodes with respect to the total, the network is heterogeneous and susceptible to loss of connectivity if one of the most important nodes is disconnected.

The above indicators are unknown in the original data set. It is possible to determine them because they are part of the network topology statistics. Before we can obtain them, however, the style of the SPI payment system database must contain a variable indicating who sends the payment and another indicating who receives it. In this way and without network representation, a connection is established between these participants. This connection will be represented through the links between all the SPI participants, where we will be able to know which are the most relevant ones through the centrality indicators per node, but the structure of the network in general will also be known through structural network indicators.

Therefore, the original SPI information detailing who sends a payment and who receives it allows us to develop the network topology as the real connections between financial entities are also known. If we did not know explicitly who sends and who receives the payment, we would not be able to apply network topology, much less obtain its indicators.

3.2. k-*medoids algorithm*

Diaz (2007), Bramer (2016), Hastie et al. (2017), and Pardo (2020) point out that the algorithm of *k*-medoid agglomerates to the most similar nodes in the number of preset clusters, where the similarity between nodes is given by the smallest distance to the representative node of each cluster. When partitioning with *k*-medoids, it is advisable to use the partitioning around medoids (PAM) method because it minimizes the sum of the difference of each node relative to the representative node. Mathematically, the *k*-medoid algorithm can be summarized in Eq. (1).

$$C(i) = \sum_{k=1}^{K} \min_{1 \leq n \leq N} d_{ii_k^*} \tag{1}$$

This equation points out that the union of the $i-th$ node to cluster k is given only if, there is the slightest distance between it and the representative node of cluster k ($d_{ii_k^*}$). The *k*-medoid method is also most effective in the presence of outlier data, so it is more highly recommended than the *k*-means method.

The indicators of node centrality are the new information obtained because of the network topology methodology. That is, they are characteristics that we did not know before about each participant in the payment network. Therefore, this information will be used through the *k*-medoid algorithm to determine groups in the SPI payment network. Thus, the heterogeneity in this type of network will be made explicit with the formation of clusters whose members will be most like each other, but different with respect to the members of other groups.

Clusters will be formed according to the information on centrality indicators per node—that is, financial institutions that are similar in terms of connectivity will be grouped together. The similarity between these will be approximated with the distance (considering all centrality indicators) to the representative node of each group determined in the *k*-medoid PAM algorithm.

Both the representation of the SPI payment system in network topology and the estimation of clusters according to centrality indicators per node will be determined using the Rstudio graphical and data analysis interface. With the primary information of payments made between financial entities, we will represent the SPI in network topology, determining structural and centrality indicators per node. The latter, being the input to determine the clusters in the network, and thus corroborate the heterogeneity between financial entities belonging to the same payment system. In addition, this result (together with the interrelation coefficient) helps us to know which financial entities are the most systemically important (given their connectivity), since the simulations will be carried out on these entities, where each one is excluded and the SPI payment network is recorded in its absence.

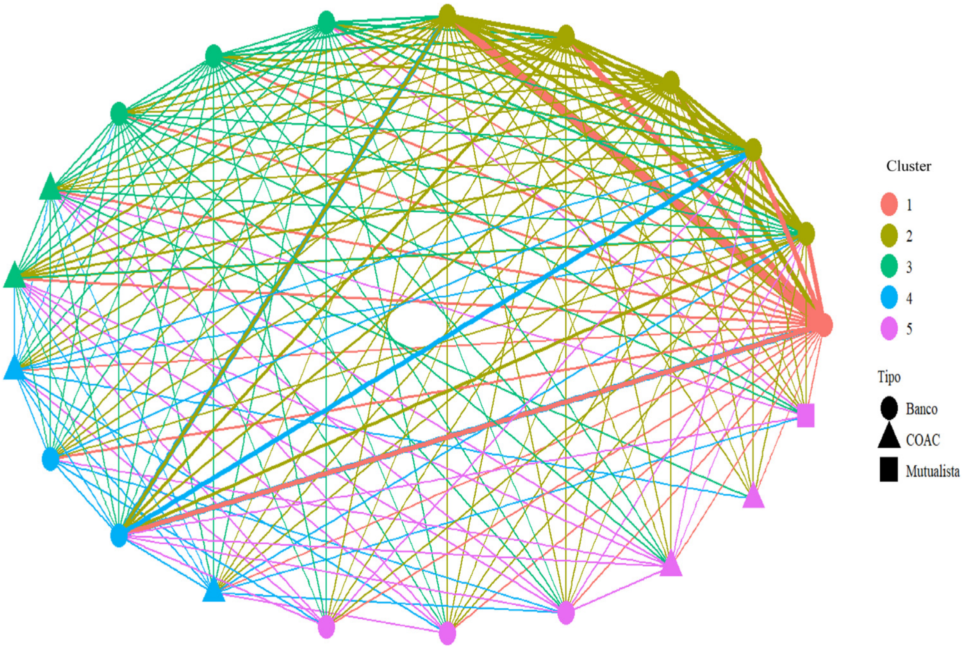


Fig. 1. Annual Network Payment System 2019
Note: The network has only 21 entities of the 55 in total for better visualization because considering all the financial entities makes it difficult to see links and nodes.

Table 1
Structural indicators of the SPI network.

Temporality	Annual	Minimum month	Average month	Maximum month	Day with the highest number of operations	Day with less amount	Day with the highest amount
Active Nodes	55	54	55	55	54	53	54
Density	77%	59%	62%	65%	42%	30%	35%
Distance	1.23	1.36	1.38	1.42	1.54	1.67	1.63
Diameter	2	2	2	3	2	3	3
Transitivity (grouping coefficient)	89%	80%	81%	82%	69%	58%	65%
Reciprocity	91%	83%	85%	87%	73%	69%	70%
Amount (USD million)	71,989	5,608	6,082	7,000	747	353	988
Average Input Links	42	32	33	35	22	16	19
Average Output Links	42	32	33	35	22	16	19
Volatility Input Links	11	12	13	14	11	10	11
Volatility Exit Links	10	13	14	14	16	15	15

Source: SPI Data in Network Topology

4. Results

This section shows the results of the characterization of the SPI network and its metrics by financial institution to determine the level of importance of each and identifies the systemically important ones. Subsequently, groupings are made between similar financial institutions. Fig. 1 shows how a few entities (nodes) have more robust payment relationships (links) than others. These are the ones with the greatest connectivity in the network.

4.1. Characterization of SPI's network

Table 1 shows the structural indicators of the SPI payment network at various time periods. It also shows a high monthly average density, where 62% of the possible connections are executed. The minimum distance shows that at least 1.38 connections (links) are needed to channel transactions between two financial institutions to the SPI payment network, reflecting an almost direct relationship among all financial institutions. The diameter indicates that normally the maximum number of transactions between two SPI participants to make a payment is two connections. The clustering coefficient of the SPI network shows that 81% of the pairs of participants (nodes) connect to a third participant and in turn connect to each other. This reflects a high degree of concentration, and those financial entities that do not have a direct connection with the rest need a highly connected entity to do so. There is also a high

Table 2
Structural indicators of the SPI network.

Temporality	statistical	# links in	# links out	Betweeness	Closeness	Authority	Eccentricity In	Eccentricity Out
Annual	maximum	54	54	57	1	1	2	2
	average	42	42	12	0.8	0.81	1.87	1.98
	minimum	2	16	0	0.59	0.19	1	1
Monthly	maximum	54	54	182	1	1	3	3
	average	33	33	21	0.8	0.7	1.96	2.03
	minimum	1	0	0	0	0.5	0.01	1
Increased number of operations	maximum	47	53	257	1	1	2	2
	average	22	22	26	0.7	0.6	2	2
	minimum	2	0	0	0.5	0	2	0
Higher amount	maximum	46	51	290	1	1	3	3
	average	19	19	30	0.7	0.5	2	2
	minimum	1	0	0	0.4	0	2	0
Less amount	maximum	43	52	480	1	1	3	3
	average	16	16	31	0.6	0.5	2	2
	minimum	1	0	0	0.5	0	2	0

Source: SPI Data in Network Topology

level of reciprocity in the SPI payment network because 85% of the possible connections between participants are bidirectional—that is, financial institutions order and receive transactions from each other. This reflects that there is symmetry in the relationships of the participants.

The network indicators in specific events such as the day with the highest number of transactions and the day with the lowest and highest amount channeled in the year analyzed show that the level of disconnection within the payment network of the SPI deteriorates on the day with the lowest amount channeled by the SPI. This is because the network can reach up to 70% of the expected flows (density), three maximum connection steps between two participants, a level of reciprocity of 69%, all explained by the reduction to almost half of the incoming and outgoing links in the payment network. Appendix A, shows the 2019 monthly network properties where one can observe that the first half of the year is characterized by lower network stability (as measured by distance) relative to the second half of the year. The second half of the year is characterized by more stability with a higher level of reciprocity and a higher density—that is, it has a higher number of connections among other factors.

The results of the average minimum distance and diameter, show that payment transactions are fast—that is, payment between clients of different financial firms does not take long, which points to the efficiency of the SPI. In addition, the high degree of concentration and reciprocity suggests that money continues to circulate in the SPI payment system between different financial institutions. This is beneficial as it shows confidence on the part of clients that use the SPI as well as good functioning of the SPI and a sign of how the amount of money is kept as an alternative means of payment to physical money.

The results of the SPI network centrality indicators are shown in Table 2 below. With these metrics, the behavior and relevance within the network per node or financial institution may be understood, where higher or lower connectivity implies high or low node relevance. The results obtained reflect heterogeneity between the nodes (participants) of the SPI network. [1]

Degree centrality shows that the maximum number of possible connections or links of an entity or node is with 54 other entities or nodes, the total number of financial institutions analyzed in this study. In the SPI network, in year one, entity channels operated with another 42 entities out of 55 possible on average. In the month with 33 participants, participation reached on average 16 participants on the day that the least amount was channeled by the SPI. We observed that there are highly connected entities (maximum) while there are others with an almost zero connection (minimum).

Betweenness centrality indicates that in the SPI network in one month an entity on average is used 21 times as a connector between two other participants. The day the smallest amount was channeled by the SPI, an entity was used about 480 times as a connector, being a key financial institution for the SPI payment network to remain united. Meanwhile, on the day with the highest number of operations in the SPI, some entity was used to connect 257 times. This reflects that as the network disconnects, they are more dependent on fewer financial institutions to keep the payment network together. There are 5 participants who have never been a connector between entities (3 banks, 1 COAC and 1 mutualist), while most entities are connectors at least one time.

The **closeness** of the SPI payment network shows that the average distance of a participant (node) to the rest of the participants is 0.8, where only 9 financial institutions reach a coefficient equal to unity. The entities with the lowest level of connection, are farther away from other financial institutions, so that they need others to connect. In other words, they require the nodes with the highest coefficient of proximity since these are the most connected.

The **average** authority of the SPI payment network is 0.7. Most entities have a high level of importance or authority within them. There are 6 entities that have a higher level of authority, which reflects that many participants link to these nodes or other participants. There are certain entities that do not represent any level of authority within the network (0).

[1] The heterogeneity between nodes appears to be constant and maintained over time, a unit root test was performed with global indicators in 2019, where no significant differences were found, suggesting that the SPI network is structural (see annex B).

Table 3
Average centrality metrics per conglomerate.

Conglomerate	Nodes (Entities)	Average								
		# Links in	# Links out	Betweenness	Closeness	Authority Score	Eccentricity In	Eccentricity Out	Amount	Operations
1	1	53	54	136.13	1	1	1	1	1,345.02	773.32
2	6	52	50	68.92	0.98	0.99	1.67	1.99	588.13	251.30
3	14	43	45	31.53	0.91	0.89	2	2.01	27.03	23.31
4	16	32	33	7.89	0.78	0.71	2	2.05	41.67	3.63
5	18	20	17	0.84	0.65	0.43	2.02	2.1	1.65	1.06

Note: The amount and number of trades were not part of the variables for clustering. The amounts are in millions and the trading figure is in the thousands.
Source: SPI Data in Network Topology

The **eccentricity of a node,** indicates that in the SPI, the maximum distance between participants to relate on average is two input and output connections. However, there are participants who can have up to three connections to relate to another participant and other nodes so that their maximum distance is 1, which is usually the most connected participants.

Earlier, we indicated that the SPI payment network is shown to be efficient, as payments are executed quickly. However, centrality indicators reveal that this fast payment transactionability is due to a subset of all financial institutions. They benefit from being the dominant ones in terms of connectivity because they concentrate the payment network. Such concentration gives them market power not only in connectivity, but also in profits because by receiving and issuing more payments than this, their profits grow, while the less connected financial entities would not have the same result. Rather, they depend on the dominant ones to make payments so that their market share and profits are lower. In other words, we have a scheme where the most connected continue to consolidate. In fact in the case of Ecuador's SPI, we can see how a single financial entity dominates the payments market, which together with those of the second conglomerate could form a payments oligopoly, as they are robust financial institutions that are very different from the rest.

Table 3 shows the groupings of financial institutions that have similar behaviors among themselves (determined by their centrality metrics) according to the non-hierarchical *k*-medoids[2] method, which recommends five clusters [3] among the 55 entities analyzed. This analysis allows one to identify the level of heterogeneity among nodes or financial institutions in the SPI payment network and too determine whether there are COAC-like banks and vice versa. This is determined by their behavior within the payment network.

The first two groups represent systemically important financial institutions (7) in the SPI network, channeling 98% of the amount and operations. They are characterized by trading with all financial institutions and are an important link to keep the network connected. The third group of financial institutions (17) channel 1% of the total amount in the SPI. We observe in this group that there are banks such as COAC and others that have a level of connectivity with 78% of participants on average. The last two clusters contain the least connected financial institutions (34) in the SPI network. These include banks and COAC that channel about 2% of the total amount in the SPI. They connect with about 58% of participants on average and are not normally used as connectors. The latter are highly dependent on the entities of the first groupings (Croig and Von Peter, 2014; Fricke and Lux, 2014). These results corroborate the heterogeneity between financial institutions in the SPI. As an example, Fig. 2 represents the five groupings in relation to the number of times the financial institution was used as a connector in the SPI network and depending on the amount channeled. Groups with five colors are represented and differentiate between banks, COAC and mutualists with circles, triangles and squares respectively. The evidence shows the divergence between financial entities in the SPI payment network. Most of them have low connectivity, and a few have high connectivity, which benefits them in a greater channeling of the amount paid. This further consolidates them as systemically important entities while making the SPI payment network more sensitive to financial contagion.

4.2. Simulation of network exclusion of payments from systemically important entities in the SPI

The simulation was performed on the graphical and data analysis interface Rstudio, whose logic considers five iterations, in the first of which most SPI participants were connected (Table 4). The one that executed the largest amount of payments (Table 5) is excluded. How the network reacts is recorded through centrality metrics. That is, the resulting payment network only considers 53 financial institutions. Then, in the second iteration, we again exclude the entity that among the remaining 53 is the one with the highest connectivity and amount paid (Tables 4 and 5 respectively), and it records the response of the centrality metrics and ends up with a network of 52 participants. Thus, the financial institution with the highest connectivity (Table 4) and the amount of payments executed (Table 5) among the existing nodes is sequentially excluded until we end up with a network of 49 nodes. In other words, in the fifth iteration, the 5 most relevant entities in terms of connectivity (Table 4) and amount paid (Table 5) were excluded.

[2] Non-hierarchical methods are characterized by requiring the number of clusters to be specified prior to their estimation, where the *k*-medoids algorithm is widely recommended as it is most effective in estimates with outliers. Because the heterogeneity in node connectivity is considerable, this method was used. See robustness tests in Annex C.

[3] Group 1: 1 bank, Group 2: 6 banks, Group 3: 7 banks – 6 COAC and 1 mutualist; Group 4: 4 banks and 12 COAC; Group 5: 6 banks, 8 COAC and 3 mutualists.

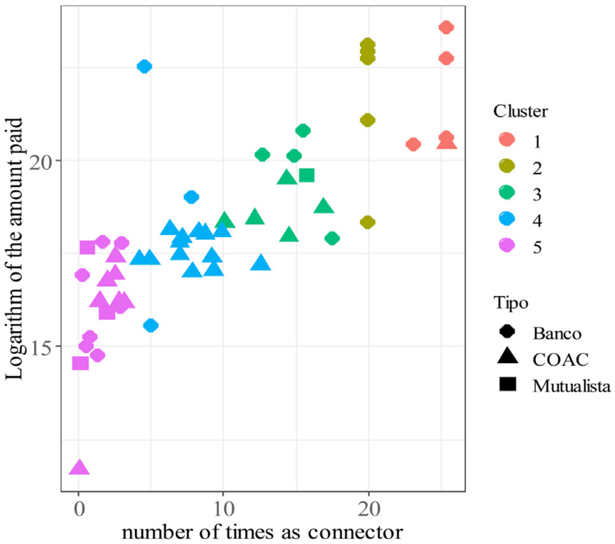


Fig. 2. SPI network by conglomerates in 2019
Note: The circles represent banks; triangles are the COAC, and the squares are mutualists. Y: Number of times as connector; X: Amount transacted by SPI.
Source: SPI Data in Network Topology

Table 4
Network Stability excluding 5 participants with greater connectivity (Annual Network).

Excluded EFIS	Active banks	Minimum Distance	Amount	Diameter	Transitivity	Reciprocity	Density
0	55	1.23	100%	2.00	88.80%	90.86%	77.00%
1	54	1.24	77%	3.00	88.45%	90.41%	73.37%
2	53	1.25	68%	3.00	88.07%	89.97%	69.83%
3	52	1.26	53%	3.00	87.68%	89.50%	66.36%
4	51	1.27	42%	3.00	87.28%	88.98%	62.96%
5	50	1.28	32%	3.00	86.85%	88.55%	59.70%

Source: SPI Data in Network Topology

Table 5
Network Stability excluding 5 participants with the highest transactional amounts (Annual Network).

Excluded EFIS	Active banks	Minimum Distance	Amount	Diameter	Clustering	Reciprocity	Density
0	55	1.23	100%	2.00	88.80%	90.86%	77.00%
1	54	1.24	77%	3.00	88.45%	90.41%	73.37%
2	53	1.25	62%	3.00	88.07%	89.97%	69.83%
3	52	1.26	51%	3.00	87.68%	89.50%	66.36%
4	51	1.27	40%	3.00	87.28%	88.98%	62.96%
5	50	1.28	31%	3.00	86.85%	88.55%	59.70%

Source: SPI Data in Network Topology

It simulates the exclusion of systemically important participants in the SPI network to assess the stability of the payment network and see its effect on the total liquidity transferred in the SPI. The first scenario (Table 4) simulates the elimination of the 5 participants with the highest degree of total connectivity (greater number of connections), and in the second scenario (Table 5) the elimination of the five participants with the greatest participation in the value of the channeled payments, as in the exercise conducted by Cepeda (2008). In the case of the SPI, it is noted that the majority of participants who are most connected (a greater number of connections) are those that channeled the most payments, since only one financial entity is different between the two scenarios, hence the similarity of the results below. Therefore, except for the amount paid and network density, the results for minimum distance, diameter, transitivity and reciprocity are similar as the excluded institutions are part of the same group. It should be noted that these attacks (non-participation of participants and exclusion) could be explained by operational failures, insufficient liquidity, failures in communication infrastructure, or financial contagions, among other factors (Cepeda, 2008; Cáceres *et al.*, 2012).

The results reflect that as the two scenarios of participants are excluded, the amount channeled by the SPI is significantly reduced, and network instability increases along with distance). In the case of financial contagion (simultaneous exclusion of the 5 participants), the amount channeled by the SPI would have a drastic reduction of around 68%. The loss of stability in both cases is like increasing

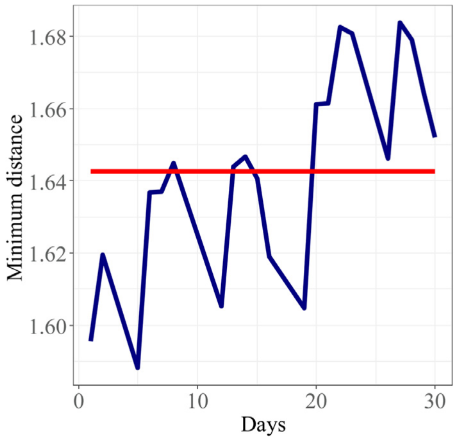


Fig. 3. Minimum distance in March
Source: SPI Data in Network Topology.

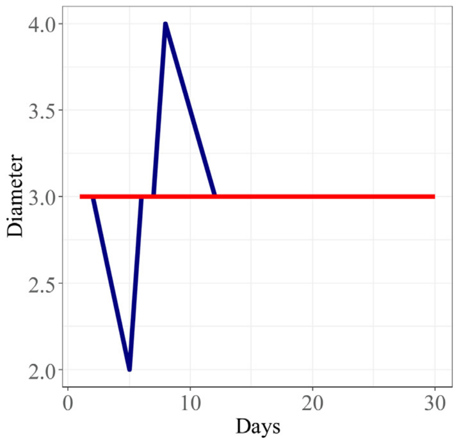


Fig. 4. Diameter in March
Source: SPI Data in Network Topology.

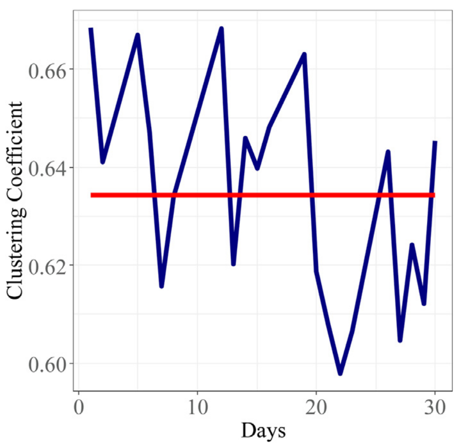


Fig. 5. Clustering in March
Source: SPI Data in Network Topology.

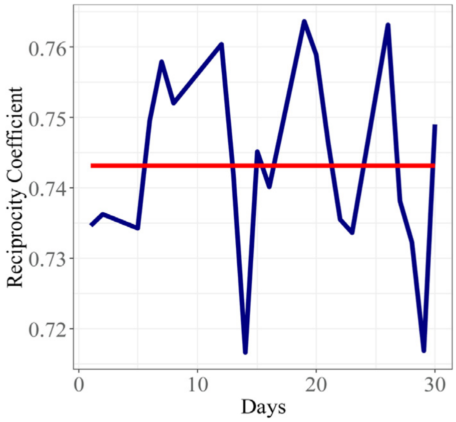


Fig. 6. Reciprocity in March
Source: SPI Data in Network Topology.

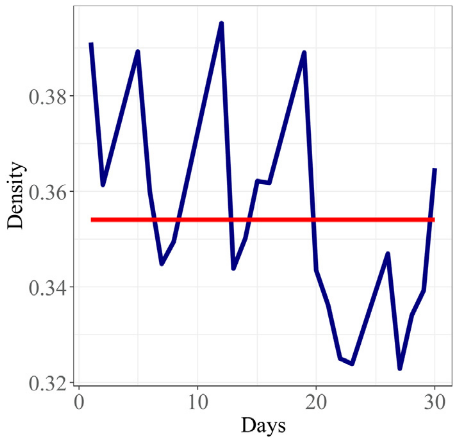


Fig. 7. Network density in March
Source: SPI Data in Network Topology.

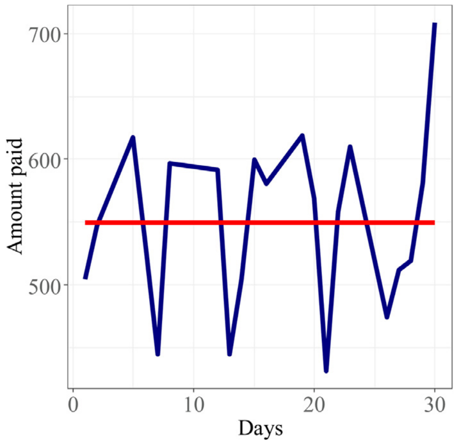


Fig. 8. Amount paid on the network in March
Source: SPI Data in Network Topology

the average distance by 4%. This reflects that the SPI payment network is highly sensitive to disconnection or failure in any of these nodes or participants.

4.3. Evaluation of the payment network at the Start of COVID pandemic confinement (March 2020)

The SARS-COV-2 (COVID-19) pandemic has slowed the overall economy, at least in the early months of 2020. Therefore, by examining how the SPI unfolded, it can be determined that there was a loss of stability in the payment network—it became slower to make payments, especially since March 18, as the number of connections have increased (minimum distance in Fig. 3 and density in Fig. 7). However, we also have a lower concentration and reciprocity in the SPI payment network (Figs. 5 and 6)—that is, money circulated in the payment system in smaller amounts (Fig. 8), which is the result of the paralysis of activities or the population, due to uncertainty, withdrawing their cash deposits.

5. Conclusions

The functioning of the financial system is strongly supported by the proper functioning of payment systems. The monitoring and control of payment systems is one of the main objectives of central banks. In this context, several countries have built and implemented tools to monitor, detect and analyze possible risks that may arise in the payment system. We provided an effective tool for the Ecuadorian case in the SPI.

The results obtained from the combination of network topology models, clusters, and simulations allowed us to characterize the SPI payment network and to evaluate its stability during stress events. It also allowed for a more accurate analysis of systemic risk. It was determined that the SPI network has a high density (32% of the possible flows are not connected), but on specific days, such as the days with the highest and lowest amounts channeled or the highest number of operations, the disconnection of flows approaches 50% of the payment network. This shows that there may be a concentration on certain flows among some participants to keep the payment network connected. An important feature is the high level of reciprocity between payment flows in the SPI; 85% of payment flows are back and forth between financial institutions. This means that payments were sent back to the financial institutions from which they were issued so that money continues circulating in the payment system.

In addition, the participation of financial institutions in SPI networks is heterogeneous, as they have more connected participants (major/central) than others. The main criterion for ranking systemically important players is based on intermediation capacity, which involves the use of metrics such as Betweenness centrality, closeness and authority. Furthermore, by using the K-means methodology on centrality indicators, we learned that in the SPI there can be 5 groups that encompass similar entities in their behavior within the SPI network—some banks behave like cooperatives. The number of connections and the amounts channeled were also analyzed to determine their participation in the SPI. In Ecuador there are 7 main financial institutions that are systemically important; these financial institutions are the ones with the greatest impact on the network, in case of possible problems. For the simulations we excluded five systemically important financial institutions from the SPI payment network, and the results showed that the payment network is highly sensitive to the disconnection or failure of these participants. We also developed an application for the network topology tool during the height of the pandemic (March 2020) when the first days of confinement caused a loss in the stability (payment execution delinquency) of the SPI payment network as the lowest channeled day in 2019.

These results are consistent with the literature, as in the reviewed papers, the payment systems were also sensitive to the disconnection of their systemically important participants. This is typical of heterogeneous networks, which were determined by means of clusters among financial institutions, thus knowing how deep the differences are in connectivity among the participants of the SPI payment network. This in turn, provides guidance for monitoring and regulatory institutions to whom financial institutions represent a potential financial contagion.

The proposed tool could support financial stability policies by monitoring the liquidity of financial institutions in a few minutes through analysis of the movement of payment flows in the SPI. In this way, the identification and monitoring of systemically important financial institutions, estimation of the variation of settled flows and amounts, stability, and sensitivity of the network can be performed to prevent or control possible financial contagion and adverse shocks. Finally, future studies could include the question of determining financial contagion and the behavior of the SPI payment network in the full year with the COVID pandemic.

Declaration of Competing Interest

The authors declare that there is no conflict of interests regarding the document sent to the Latin American Journal of Central Banking.

Moreover, the publication of the Document “Risk monitoring in Ecuador’s Payment System: implementation of the network topology” in the Latin American Journal of Central Banking has been accepted by the authors.

Appendices

A. Monthly structural indicator charts in 2019

The figures below show how the structural indicators in the SPI changed monthly in 2020. That is, their behavior is not the same over time, especially in the second half of the year, where participants (nodes) become more connected to each other (density), so that they transact payments faster (minimum distance), which keeps the SPI circulating (transitivity and reciprocity).

However, these changes over time do not become significant enough to say that the behavior between months is statistically different (KPSS test). Therefore, the heterogeneity among financial institutions and the sensitivity of the SPI payment network to the exclusion of its most connected financial institutions is maintained in each month of the year. That is, it is sensitive at all times to financial contagion.

B. Stationary test in KPSS criterion on global indicators

The table below shows the value obtained from a KPSS test to check the stationarity of the structural indicators in the network. These, except for density, are less than 0.05, thus indicating that only the density of the network shows significant changes over time, while the minimum distance, diameter, transitivity and reciprocity do not. That is, the SPI payment network has a variation in total connections between months, but it does not stop being concentrated or executing payments quickly.

Metric	KPSS_pvalue
Minimum distance	0.060
Diameter	0.100
Transitivity	0.068
Reciprocity	0.044
Density	0.039

Source: SPI Data in Network Topology

C. Selection of the number of optimal clusters

It is difficult to select how many clusters to use in a data set because the number of clusters is not known a priori. But the results following the elbow method (Charts A6.1 and A6.2), according to the most common frequency of information criteria (Figure a7). Silhouette adjustment (Figure a8) allow us to find the optimal number of clusters that best classifies financial institutions according to their centrality indicators.

Chart A1, A2, A3, A4, A5, A7 and A8

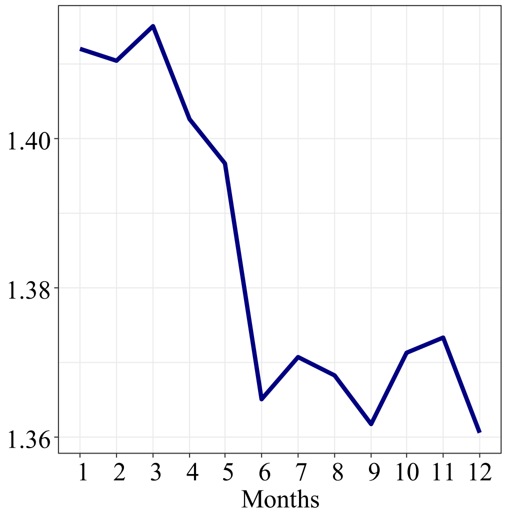


Chart A1. Minimum distance in time
Source: SPI Data in Network Topology.

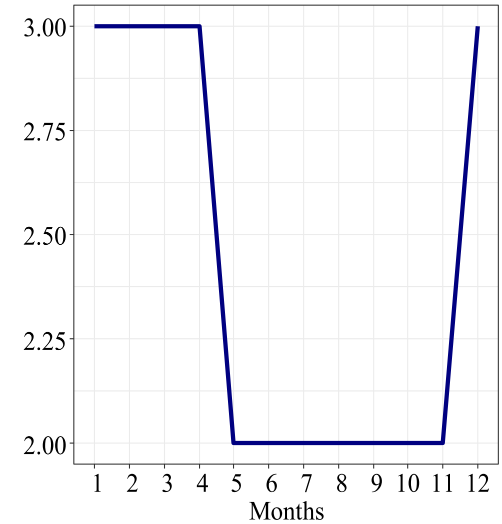


Chart A2. Diameter in time.

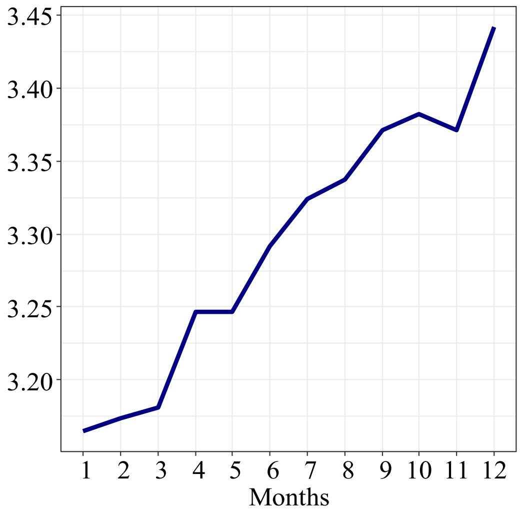


Chart A3. Density over time
Source: SPI Data in Network Topology.

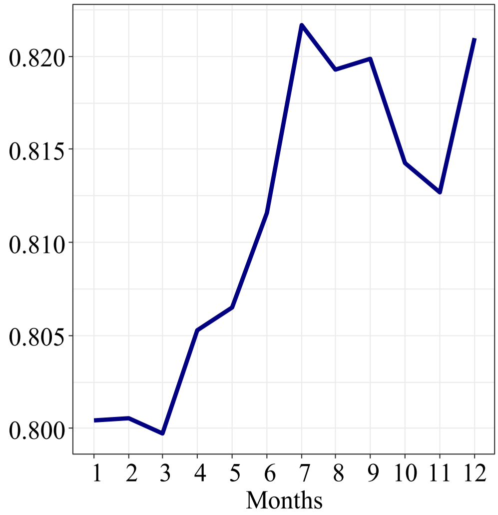


Chart A4. Clustering Coefficient.

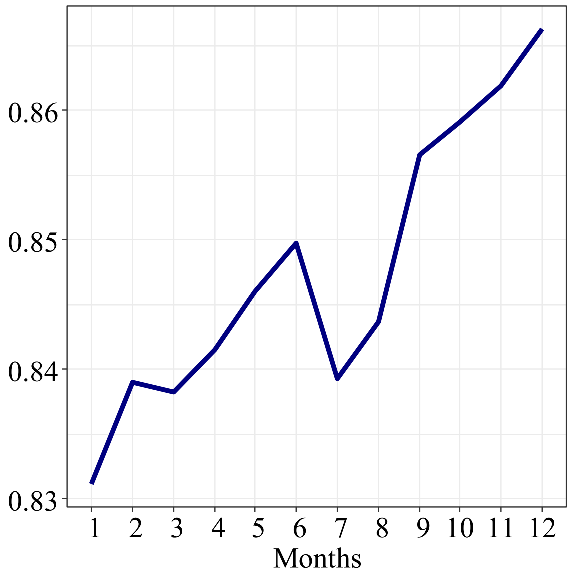


Chart A5. Reciprocity over time
Source: SPI Data in Network Topology.

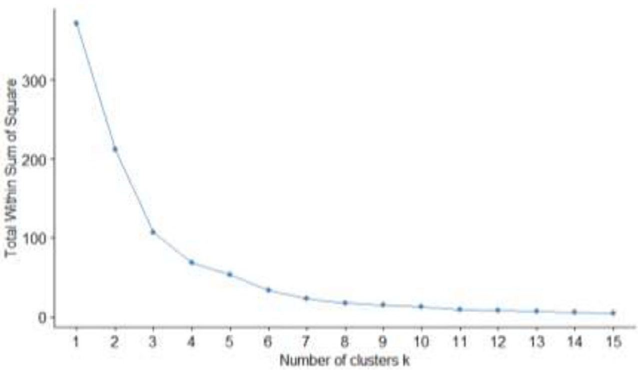


Chart A6.1. Number of optimal clusters with Euclidean distance
Source: SPI Data in Network Topology.

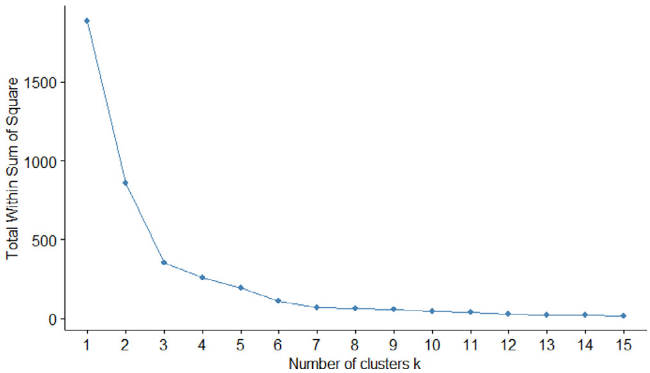


Chart A6.2. Number of optimal clusters with Euclidean Manhattan distance
Source: SPI Data in Network Topology.

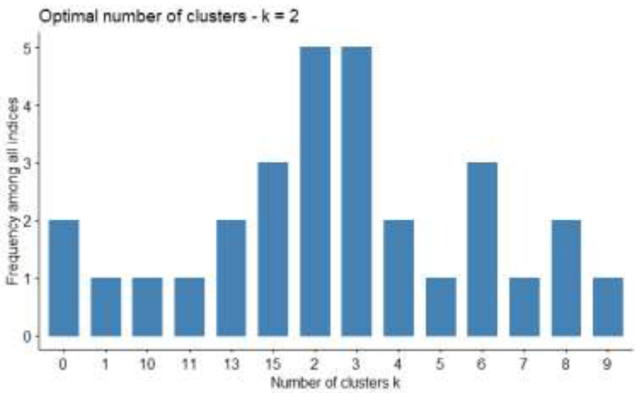
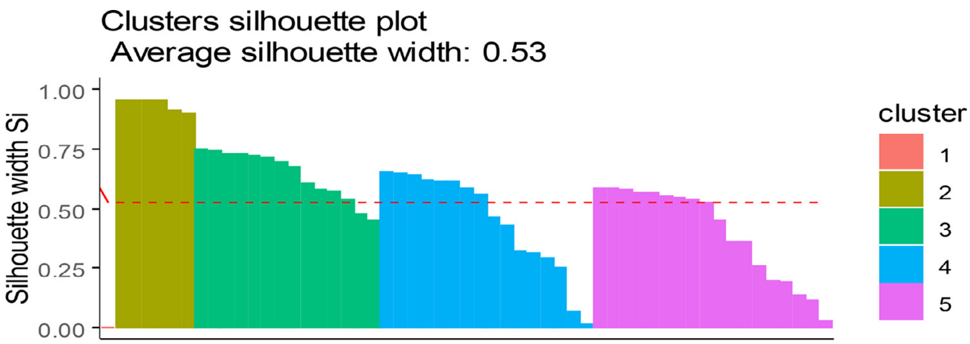


Chart A7. Optimal number of conglomerates according to information criteria
Note: In the NbClust package, there is no option to evaluate the selection criteria in *k*-medoids, but since this classification method is analogous to the medium and robust in the presence of atypical data, the Euclidean distance and the median classification method were established as a measure of similarity, to obtain a result similar to the *k*-medoid PAM method.
Source: SPI Data in Network Topology.



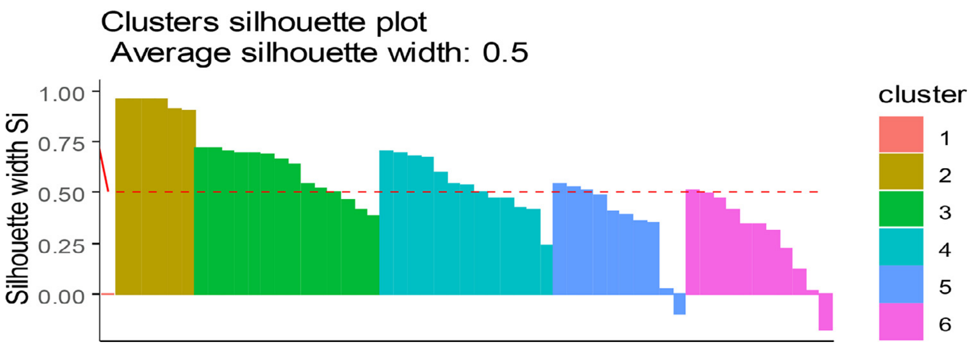


Chart A8. Quality of conglomerates in *k*-medoids
Note: The first class consists of an object and therefore does not appear with k-5.
Source: SPI Data in Network Topology.

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