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Redundancy of Centrality Measures in Financial Market Infrastructures

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Abstract

The concept of centrality has been widely used to monitor systems with a network structure because it allows identifying their most influential participants. This monitoring task can be difficult if the number of system participants is considerably large or if the wide variety of centrality measures currently available produce non-coincident (or mixed) signals. This document uses principal component analysis to evaluate a set of centrality measures calculated for the financial institutions that participate in four financial market infrastructures of Colombia. The results obtained are used to construct general indices of centrality, using the strongest measures of centrality as inputs, and leaving aside those considered redundant.

Keywords: centrality, principal component analysis, redundancy analysis, clustering analysis.

JEL: G20; C38; C23

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Redundancia de las medidas de centralidad en Infraestructuras del Mercado Financiero

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Resumen

El concepto de centralidad ha sido ampliamente utilizado para monitorear sistemas con estructura de red ya que permite identificar a los participantes más influyentes. Las labores de monitoreo pueden ser difíciles de realizar si el número de participantes en esos sistemas es considerablemente amplio o si las medidas de centralidad producen resultados no coincidentes o generan señales mixtas. Este documento usa el análisis de componentes principales para evaluar un conjunto de medidas de centralidad calculadas para las instituciones financieras que participan en cuatro infraestructuras de los mercados financieros en Colombia. Los resultados obtenidos son utilizados para construir índices generales de centralidad, utilizando como insumos las medidas de centralidad más fuertes y dejando de lado aquellas consideradas redundantes.

Palabras clave: centralidad, análisis de componentes principales, análisis de redundancia, análisis de *clustering*.

JEL: G20; C38; C23

1. Introduction

Financial market infrastructures (FMIs) are the systems through which the clearing, settling, and recording of transactions (payments, securities, and derivatives) take place (BIS-PFMI, 2012). The timely and efficient performance of these market infrastructures ensures the smooth functioning of the payment system, the financial system, and therefore, of the economy as a whole.[1] However, the changes that these FMIs may experience, caused by variations in the activity of the institutions that participate in these systems or by unexpected exogenous shocks, have encouraged central banks and supervisory authorities to conduct monitoring activities aimed at identifying the cases or system participants that need to be studied in more detail.

Systems with a network structure, like the FMIs and financial markets, are frequently studied using measures of centrality, since these allow to identify their most influential participant. These measures have been used to establish the systemic importance of financial institutions in payment systems (Soramäki and Cook, 2013; Baek, Soramäki, and Yoon, 2014) and unsecured interbank markets (Temizsoy, Iori, and Montes-Rojas, 2017; Rovira and Spelta, 2019). They have also been used to assess systemic risk (Battiston, Puliga, Kaushik, Tasca, and Caldarelli, 2012; Dungey, Luciani, and Veredas, 2014), monitor systemic risk (Battiston, Caldarelli, D'Ericco, Gurciullo, 2016), identify liquidity providers and liquidity hoarders in payment systems (Soramäki and Cook, 2013), and differentiate networks of financial institutions (León, Mariño, and Cadena, 2021).[2]

Centrality measures can also be very useful to monitor FMIs and warn about possible changes in their structures by identifying the relative importance of each participant in the system. But the wide variety of centrality measures currently available can make monitoring each financial institution under all measures an endless challenge, either because the total number of participants in the system is considerably large and/or because the signals extracted from the centrality measures do not coincide. We propose to simplify this monitoring task by

[1] According to the BIS, the safe and efficient functioning of FMIs is essential to guarantee the reliable transfer of funds and securities between the participants of the financial system, and to assure that the implementation of the monetary policy can spread quickly throughout the economy (BIS-PFMI, 2012).
[2] León et al (2021) found that networks of financial institutions that clear and settle their transactions through a central counterparty are more connected and closer to their counterparts than those that settle their transactions bilaterally, which naturally allows the former to reduce the liquidity and counterparty risks.

constructing general centrality indices using the most relevant measures as inputs and discarding those considered redundant. To accomplish this goal, we use principal component analysis —PCA— (Pearson, 1901; Hotelling, 1933) to examine the centrality of the financial institutions that participate in four financial market infrastructures of Colombia: the large-value payment system, the foreign exchange clearing house, and two central securities depositories. The first of these FMIs (CUD) is the conduit used by all financial institutions to transfer large-value payments. The foreign exchange clearing house (CCDC) clears and settles peso/dollar transactions. The central securities depositories (DCV and Deceval) provide services (accounts and custody) aimed at ensuring the integrity of securities in transactions (BIS-CPSS, 2003). DCV fulfils this function for sovereign debt securities and Deceval for corporate and non-sovereign government securities and equities.

In this study, each FMI is envisioned as a network of financial institutions connected to each other by transactions, either defined by payments, trades, or similar agreements. After implementing PCA on centrality measures we obtain composite centrality indices that provide relevant information about the system's participants (i.e., ranking of centrality).[3] The financial institutions identified as the most central are precisely those that, in the event of non-complying their commitments (i.e., payments or collateral delivery), can have a considerable impact on their respective network and the payment system. As in Joliffe (1972, 1973), we test how well PCA identifies redundant variables by comparing several statistical methods that also determine which variables should be retained and which should be discarded. These robustness checks include two versions of principal components based on subsamples of data, the redundancy analysis —RDA— (Kelley, 1940; Rao, 1964; van den Wollenberg, 1977), and a clustering method. This topic is relevant for the Colombian central bank (Banco de la República), as it is the authority in charge of monitoring these FMIs and ensuring the safe and efficient functioning of the payment system. The results obtained from these centrality indices can be used as tools to monitor these FMIs as they can facilitate the identification of the system's participants that can produce substantial impacts on a network or considerable changes in the network stability.

[3] The Financial Infrastructure Oversight Department is using a centrality index obtained from applying PCA to six centrality measures (i.e., in-degree, out-degree, hub, authority, in-strength and out-strength). The index presented in this work is more comprehensive as it expands the number of centrality measures to twenty-six.

The paper is organized as follows: Section 2 provides a general description of the centrality measures, and Section 3 presents a brief explanation of the statistical methods used in this study: PCA, RDA, and cluster analysis. Section 4 describes the FMIs, and Section 5 presents the main results and the rankings of the most central participants in each network.

2. Network centrality measures

In the theory of graphs, a network is a graphical representation of a complex system, composed by nodes that may (or not) be connected by edges or links. The links connecting pairs of nodes vary only when there are differences in the strength of the relationships. These cases correspond to weighted edges and allow the analyst to identify stronger from weaker links. In contrast, the strength of relationships in unweighted links do not vary for the nodes that compose the network. Similarly, the nodes in a network can be the same size when there are no differences between them, or they can have different sizes when they have been scaled by a criterion pre-established for this purpose.

A network can be described mathematically by an adjacency matrix (A) of $N \times N$ dimension, representing pairs of connected nodes (i and j) with nonzero elements, and nonconnected nodes with zeroes. In the binary case, the connected pairs are denoted with elements equal to one (A_{ij} =1), and the nonconnected are, again, represented with zeroes (A_{ij} =0). In directed networks, a nonzero A_{ij} element represents the existence of a link pointing from j to i, which is independent of the existence of a link pointing in the opposite direction A_{ji} (Newman, 2008). In undirected networks the matrix is symmetric, and hence, $A_{ij} = A_{ji}$.

The centrality concept was initially postulated by Camille Jordan in 1869 to identify the most influential node (element) in a network (Hage and Harary, 1995). Since then, several centrality measures have been proposed, ranging from count methods to algorithms used to study financial networks. This section briefly explains some of these centrality measures, assuming that the pairs of nodes are contained in the adjacency matrix A and are denoted as A_{ij}. Throughout this document the adjacency matrix A transposed will be denoted as A^T.

Degree centrality measures the connectedness of a node by the number of links to its neighbors (Barrat, et al. 2004). In its simple form, degree centrality applies to undirected networks, but there are two additional variants for directed networks: one that counts the links that point towards a node (i.e., in-degree) and another that counts the links that point outside the node (i.e., out-degree).[4] In all versions of the degree centrality measure, the count of neighbors should be adjusted by the total number of nodes ($N - 1$) with which the node under study (i) can have an interaction in the network (G):

$$Degree(i) = \sum_{j \epsilon G} \frac{A_{ij}}{N-1}. \quad (1)$$

Thus, the most central node is that with the highest number of links (Newman, 2008).

Closeness centrality indicates how near a node is to the other nodes of the network based on the length of shortest paths (Goldbeck, 2013). This measure is formally calculated by the inverse function of the sum of the average shortest distances between a node and all the other nodes in the network (Bavelas, 1950).

$$Closeness\,(i) = \frac{1}{\sum distance\,(i,j)} \quad (2)$$

In this measure, the most central nodes have the highest centrality results.

Betweenness centrality determines how often a path between two nodes must go through a given node. Betweenness centrality is calculated as the ratio of the total number of shortest paths (σ_{st}) between a pair of nodes (s and t) and the number of those paths that go through node i ($\sigma_{st}(i)$) (Batool and Niazi, 2014).[5]

$$Betweenness(i) = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}} \quad (3)$$

As a result, the most central node will be that with the highest betweenness result.

[4] Two alternative measures can be obtained by weighting these measures: in-strength (i.e., in-degree weighted) and out-strength (i.e., out-degree weighted).
[5] According to Newman (2008), a path is a sequence of nodes crossed by following links across a network.

Eccentricity centrality identifies the node that will cause the highest propagation of an effect in a network (Hage and Harary, 1995 and Batool and Niazzi, 2014).

$$Eccentricity(i) = \frac{1}{\max\{distance\ (i,j)\}} \tag{4}$$

This measure is assessed in three steps. The first step consists in quantifying the shortest path between a given node i and all the other nodes j in the network ($distance\ (i, j)$). The second step compares the resultant distances for every pair of nodes and identifies the maximum distance per node (i). The third step computes the inverse of the maximum distance found in the previous step. The node with the highest result will be the most central in the network.

Eigenvector centrality defines the importance (centrality) of a node by its connections to the most influential nodes in an undirected network (Pozzi et al, 2017). This iterative method of linear algebra is used to solve a general equation that in its matrix notation is of the form:

$$A^T v = \lambda v. \tag{5}$$

In the first iteration, this method assumes that the eigenvalue (λ) is a vector of ones, and from there on, it replaces the eigenvalues with the eigenvectors (v) obtained in the previous iteration, until the solution (eigenvector) converges, producing n solutions corresponding to the n values of λ. As this measure defines the importance of a node as a function of the nodes with which the former one is interacting, the most central will be that with the highest eigenvector centrality (Bonacich and Lloyd, 2001).

Hypertext induced topic search (HITS) is an algorithm used to analyze search methods in the world wide web that recursively identifies hubs (i.e., web pages that points to lots of other web pages) and authorities (i.e., web pages to which other several web pages point to). The HITS algorithm updates separate operations on the weights: one for authorities and another for the hubs. The equilibrium weights are found alternating these operations until a fixed point is reached. To this aim, an eigenvector algorithm based on matrix products defined on an adjacency matrix A of G_σ (i.e., subgraph associated with a query string σ) is computed, where the optimal weights are determined recursively, starting from initial vectors, and updating these weights with the eigenvectors computed for A^TA and AA^T. The solution to the matrix product A^TA defines the authorities and AA^T determines the hubs (Kleinberg, 1999). This algorithm is used in network analysis by redefining web pages as nodes.

PageRank is an algorithm based on the connections of web pages to the most influential web pages on the internet. It measures the probability of visiting a web page as a function of its incoming links (Brin and Page, 1998). By redefining web pages as nodes, this algorithm describes the probability that starting from node *j*, the node *i* will be visited, as can be seen in equation (6):

$$PageRank(i) = d\sum_{j\to i}\frac{page-rank(j)}{N_j} + \underbrace{(1-d)}_{dE(i)}. \quad (6)$$

Hence, the visiting probability depends on the eigenvector of adjacency matrix (A) denoted as page-rank(j), the overall number of links from node j that point to node i (N_j), the uniform distribution function (E) that makes the probability of jumping to a random node equally likely for all nodes in the network, and a parameter between zero and one (d) included to avoid traps in which sink nodes impede finding a solution.[6] The page-rank algorithm is defined recursively, computing the eigenvector P_i of matrix A at the maximal eigenvalue, with eigenvectors that are considered as probabilities. Therefore, a node will have a high page-rank if the sum of the ranks of its incoming links is high. This algorithm produces a ranking of the global importance of nodes that is called PageRank, where the nodes with high-rank probabilities will be considered the most central.

CheiRank is an algorithm that follows the same idea of PageRank, in the sense that it calculates the ranking of nodes based on their connections but uses the links in the opposite direction. Thus, the same adjacency matrix (A) of page-rank is used with the directions of all links reversed, which produces a new matrix (A^*). As the page-rank algorithm, CheiRank consists in computing the eigenvector P_i^* of A^* with the maximal eigenvalue, with eigenvectors that are considered as probabilities and are used to rank the nodes as a function

[6] This algorithm could be affected by traps that accumulates rank but never distributes any rank. The adjustment term dE(i) that is included to overcome this problem, usually takes a value of 0.15 (Brin and Page, 1998).

of the outgoing links (see Chepelianskii, 2010). CheiRank eigenvectors are also considered as probabilities of visiting nodes.

Random Walk Betweenness counts how often a node is traversed by a random walk between two other nodes (Newman, 2005). Unlike the betweenness measure that is based on shortest paths, this measure uses a random walk to generalize the betweenness idea to all nodes in the network. This measure is given by the inverse of the mean first-passage (m_{ij}) from node i to j that depends on the expected number of steps (n) taken until the first arrival to node j starting in node i and the probability that the Markov chain (i.e., probability of transitioning from node j to node i) first returns to node j ($f_{ij}^{(n)}$) in exactly n steps: $m_{ij} = \sum_{n=1}^{\infty} n f_{ij}^{(n)}$. Thus, the average importance of node j relative to the set of all nodes (R) is:

$$I(j|R) = \frac{1}{\frac{1}{|R|}\sum_{i\epsilon R} m_{ij}}. \quad (7)$$

This measure, also called Markov centrality, produces a ranking that designates the most central nodes as those with the highest results (White and Smith, 2003).

SinkRank is an algorithm that identifies systemically important banks in a payment system by executing a simulated failure of a bank and identifying the most affected counterparts (Soramäki and Cook, 2013). The node for which the SinkRank is calculated is defined as the absorbing node and all the others are the non-absorbing nodes (Baek et al, 2014). SinkRank depends on the likelihood (transition probability) that a random walk moves from one node to another, which will be different from zero for non-absorbing nodes. For absorbing nodes, that probability will be zero as it defines the termination of the walk. The SinkRank measure is formally given by the inverse of the average sink distance of each non-absorbing node, which is the same ratio between the number of non-absorbing nodes (n - m) and the sink distance of a node ($\Sigma_i \Sigma_j q_{ij}$):

$$SinkRank = \frac{n-m}{\sum_i \sum_j q_{ij}}. \quad (8)$$

In equation (8), q_{ij} denotes an element of the fundamental matrix Q that defines the number of times the random walk, located at state i, is expected to visit node j before being absorbed by a node. Thus, high sink-ranks correspond to the most central nodes, identified as those for which the simulated failure cause the strongest impact on the system.

SourceRank is a centrality measure that identifies the liquidity providers in a payment system. In general terms, source-rank is the opposite criterion to sink-rank, which is aimed at identifying the liquidity hoarders (Soramäki and Cook, 2013).

3. Some basics of statistical discarding methods

The most central financial institutions in FMIs should be monitored more closely due to the negative effects they may cause in these systems in the event they fail to meet their obligations. We use principal component analysis to identify these institutions, using the centrality measures described in the previous section. As this procedure allows the construction of a general index using individual measures of centrality as inputs, those considered redundant will be discarded. A brief explanation of the statistical techniques used to establish the centrality measures that should be retained or discarded is provided below.

3.1. Principal Component Analysis

The analysis of principal components is a statistical technique proposed by Pearson (1901) and formally developed by Hotelling (1933) to transform a set of 'n' variables into a new set of 'p' synthetic variables, which are linear combinations of the original ones. This statistical technique accomplishes a data reduction because it removes redundant (i.e., multicollinear) variables from the dataset while creating new synthetic variables —the principal components—. These 'p' new variables ($p \ll n$) explain, in decreasing order, the variation in the data not explained by the previous component. Thus, the maximum amount of variance of the original dataset is explained by the first principal component. The second principal component explains the second highest amount of variance not explained by the first component, and so forth.

For a given matrix Y, of $\mathrm{n} \times \mathrm{n}$ dimension, this method consists in computing the eigenvalues and eigenvectors of $Y^T Y$. It is considered that the selected components jointly represent the highest variance share of the original variables. There are several rules to identify the number of components to retain. We use the scaled Kaiser-Guttman test that selects the components that exceed 70% of the average eigenvalue (Jolliffe, 1972).

3.2. Redundancy Analysis

The redundancy analysis (RDA) is a multivariate analysis technique proposed by Kelley (1940) and developed by Rao (1964) and van den Wollenberg (1977) that allows to obtain a reduction in the dimensionality of data by implementing PCA on the projection of the dependent variables on the space spanned by the explanatory variables (Isräels, 1992). Since RDA combines the linear regressions and PCA, these data reduction techniques only diverge on the fact that PCA is a univariate method while RDA is multivariate. Therefore, the former method is frequently considered a special case of the latter (see van den Wollenberg, 1977).

3.3. Clustering Analysis

According to Jolliffe (1973), most clustering methods tend to produce very similar results when used for data reduction. Within these methods, the single-linkage clustering is faster than the average-linkage clustering, but none of them outperforms the other. In our robustness checks we use the average-linkage method defined on outer clustering, which selects the last variable to join the main group(s) in the cluster tree (i.e., dendrograms). This method will be implemented using the average dissimilarity of observations (i.e., the Euclidean distance) between pairs of centrality measures.[7]

4. Data description

Financial market infrastructures (FMIs) are multilateral systems that carry out the clearing, and settlement of payments, securities, derivatives, and other financial transactions (BIS-PFMI, 2012). Monitoring activities on these infrastructures may help financial authorities to

[7] The Euclidean distance is the shortest path between two points, since it is defined by a line that joins them.

detect warning signs that deserve a more profound analysis and probably specific actions to contain their potential negative effects on the system. This section briefly describes the FMIs on which the statistical analysis will be performed.

4.1. The Large-value Payment System (CUD)

The FMI that provides clearing and settlement services to institutions that send large-value payments in local financial markets is CUD, which is owned and operated by Banco de la República. This large-value payment system works in a real-time gross settlement mode, settling each transaction immediately and at its gross value, subject to the condition that the balances in the sender's account are sufficient to cover its payment orders.

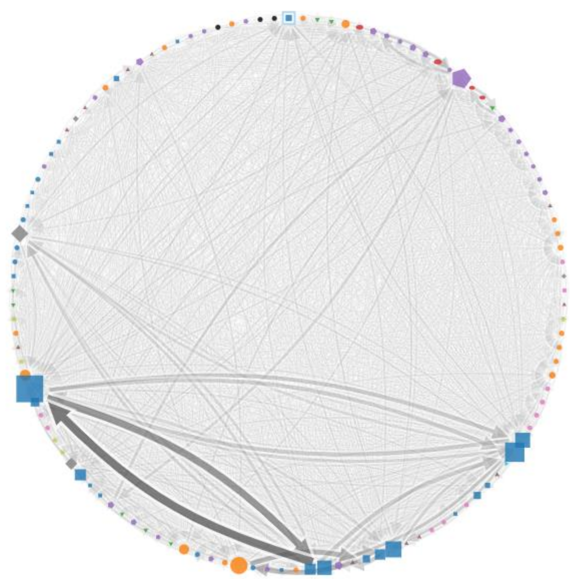


Figure 1. CUD's network with system participants represented by nodes and their transactions by links pointing the institutions receiving payments. Squared nodes represent banks, brokerage firms are circles, mutual funds are pentagons, and commercial financing companies are rhombuses. The size of the nodes corresponds to the average centrality score obtained from the hub measure. Wider links denote higher values of payments.

Several types of payments are sent through the CUD, among which are found intraday interbank funding, payments related to other clearing and settlement systems (i.e., the Foreign Exchange Clearing House (CCDC) and central securities depositories (DCV and Deceval)), government payments, and payments related to the implementation of the monetary policy.

CUD's network is presented in Figure 1, with nodes symbolizing the system's participants and links representing the average value of daily payments in a two-month period of 2020. All participants have direct access to the system and, therefore, each one of them can initiate payments without having to resort to any other institution. The average number of system's participants during 2019 was 138, of which more than 80% were financial institutions (mostly banks, trust companies, brokerage firms, and commercial financing companies).

4.2. The Foreign Exchange Clearing House of Colombia (CCDC)

The market infrastructure that provides multilateral netting and settlement services for foreign exchange transactions is the Foreign Exchange Clearing House of Colombia (CCDC). This FMI serves two functions in the foreign-exchange market. Firstly, it mitigates the risks related to foreign exchange transactions of Colombian pesos and US dollars, settled on the same day (t + 0), and up to three days after the trade (t + 1, t + 2, and t + 3). To this aim, the CCDC handles the counterparty risk by means of the payment-versus-payment mechanism. For the market risk, it requires guarantees from the participants, and for the liquidity risk it uses credit lines acquired with local financial institutions. The CCDC is not a central counterparty, and hence, in response to extreme events (such as liquidity deficits that cannot be covered by the mentioned risks mitigation mechanisms, multiple non-compliance in payment of multilateral obligations from the participants, or the impossibility that this FMI provides its services), the system participants will have to settle transactions bilaterally.[8] Secondly, CCDC facilitates the liquidity savings that result from multilateral netting.[9]

[8] From December 14, 2020, the FMI in charge of providing the clearing services for the peso/dollar transactions is the Colombian Central Counterparty (i.e., Cámara de Riesgo Central de Contraparte S.A.). However, it was not until February 1st, 2021, that these services began to operate through the novation process. As this document started long before that change, the results for these transactions are solely based on data from the CCDC.

[9] During 2019, the average daily liquidity savings that emerge as a result of the multilateral netting procedure was 86%, which signifies that system's participants paid only 14% of the gross value of transactions.

Figure 2. CCDC's network with participants represented by nodes, and their bilateral transactions by links pointing to the institutions that receive the amount of US dollar purchased. Squared nodes represent banks, brokerage firms are circles, and financial corporations are rhombuses. The size of the nodes corresponds to the average centrality score obtained from the hub measure. Wider links denote higher gross values of foreign exchange transactions.

The CCDC's network representation is shown in Figure 2, with its participants as nodes, connected through links that denote the average daily of bilateral US dollar sold amount, in a two-month period of 2020. In CCDC participate 33 financial institutions (mostly banks and brokerage firms), all with direct access to the system.

4.3. The Central Securities Depository (DCV)

Two central securities depositories are responsible for the clearing and settlement services of securities transactions in the domestic market: The Central Security Depository (DCV), and the Centralized Securities Depository of Colombia (Deceval).[10] The securities depository for local sovereign securities DCV, is a settlement system owned and administered by Banco de la República. In this system, the settlement of transactions is based on the delivery versus payment mechanism and is conducted in real-time on the large-value payment system (CUD). The access of financial institutions to DCV is also determined by the central bank and can take one of two forms: as a direct depositor (i.e., accepted as holder of securities in their own

[10] These securities are currently mostly represented in a dematerialized (electronic) form.

position or in the position of third parties), or as an indirect depositor (i.e., accepted as the holder of a subaccount) through one of the direct depositors.[11]

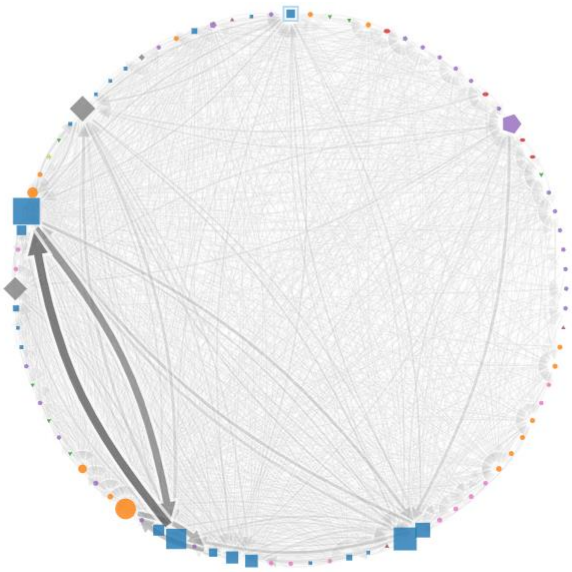


Figure 3. DCV's network with participants represented by nodes and their securities transactions by links pointing the institutions receiving liquidity. Squared nodes represent banks, circles are brokerage firms, pentagons are mutual funds, and rhombuses are financial corporations. The size of the nodes corresponds to the average centrality score obtained from the hub measure. Wider links denote higher values of transactions.

The network representation of this FMI, shown in Figure 3, was constructed using daily average data of the securities transactions in a two-month period of 2020. The average number of direct depositors in DCV during December 2019 was 126, mostly represented by pension and severance funds, banks, trust companies, and the public sector.

4.4. The Centralized Securities Depository of Colombia (Deceval)

Deceval is the privately-owned securities depository and securities settlement system, which provides deposit, clearing, and settlement services for corporate and non-sovereign government securities, along with depository services for the equity market. This depository

[11] During 2019, DCV settled a daily average of 2,122 operations and COP 39 trillion in nominal value. Of this, 6 billion corresponded to the primary market, COP 19 trillion to the secondary market and COP 20 trillion to monetary operations (services provided to the Banco de la República, which involve open market operations and liquidity provisions to the large-value payment system). This depository held COP 323 trillion at the end of 2019, of which 97% corresponded to securities issued by the national government and the remaining to securities issued by the Fund for Financing the Agricultural Sector (3%).

classifies its depositors in direct (i.e., financial institutions supervised by the Financial Superintendency of Colombia, public entities, issuing entities with securities registered in the national securities registry, intermediaries that have entered into a deposit agreement with Deceval, and other centralized securities depositors) and indirect (i.e., persons who cannot be direct depositors by regulation and can only sign a contract with a direct depositor).[12]

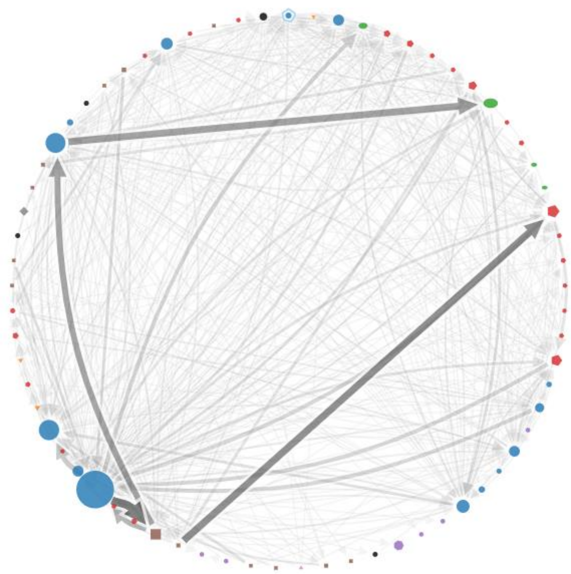


Figure 4. Deceval's network with participants represented by nodes and their securities transactions by links pointing the institutions receiving liquidity. Squared nodes represent banks, circles are brokerage firms, pentagons are mutual funds, and rhombuses are financial corporations. The size of the nodes corresponds to the average centrality score obtained from the hub measure. Wider links denote higher values of transactions.

Deceval's network is shown in Figure 4, with nodes and links between nodes representing daily average data for a two-month period of 2020. As in the former FMIs, participants are represented by nodes and their transactions by links connecting pairs of nodes. The average number of direct participants in Deceval during 2019 was 71.

We examine twenty-six centrality measures for each FMI and use them to construct general indices of centrality. These measures were calculated using daily data (from January 2, 2019,

[12] In 2019 the transactions carried out in Deceval, including primary and secondary market operations (fixed and variable income) and money market operations (repos, sell/buy-backs and securities lending) with their respective reverse transactions and cash guarantees, represented a daily average of 5,239 operations and COP 3.75 trillion. As a depository, at the end of 2019 this system held COP 561 trillion, 58% of which corresponded to equities (ordinary and preferential), 23% to term certificates of deposits, 10% to ordinary bonds, and 9% to other instruments (commercial papers, acceptances, among others).

to August 31, 2020) of the payments settled through the CUD, the gross value of peso/dollar transactions for the CCDC, the securities transactions for DCV, and the transactions' value of purchase and sales, sell/buy-backs and repurchase agreements for Deceval. The entire set of centrality measures corresponds to the alternatives supported by the theory, which means that in their calculation it was considered whether they should be based on directed or undirected networks, as explained in Section 2. These measures are considered in their weighted and unweighted forms. The former versions of these measures were calculated using the value of daily transactions between participants of the system as weights. Summary statistics of these measures are provided in Table A.1 in the appendix. As can be seen in that Table, the total number of observations for the sample period is larger for CUD (46,303) than for CCDC (12,939), DCV (24,135), and Deceval (18,999). However, the effective number of observations is slightly shortened due to the existence of gaps in some centrality measures.[13] All centrality measures were transformed into its percent participation per day so as to avoid that differences in the measurement units will alter the results.[14]

5. Redundant centrality measures

One of the most used tools for monitoring networks are the general centrality indices, as they facilitate the identification of nodes that should be examined more carefully due to their relative importance in the system. As these indices are generally based on an extensive data set, it is necessary to know which variables should be retained and which should be discarded considering the level of information they provide. In this case, the redundant variables are defined as those that do not provide additional information on the centrality of the FMI's participants. We use PCA on the correlation matrix of these measures to identify and discard those considered redundant and to construct general indices of centrality.

[13] Data loss may arise from networks with links that do not allow the calculation of centrality measures given that the network's data do not adjust to the algorithm and/or its restrictions. That is the case of weakly connected nodes, for which some centrality measures either cannot be computed or produce a result that tends to infinitum.
[14] Similar results were obtained when the usual standardization (i.e., zero mean and unit variance) was applied to the data set.

5.1. Results based on PCA

Prior to the statistical analysis with PCA, we checked whether this method could be applied to these FMIs by calculating the overall sampling adequacy test (i.e., Kaiser-Meyer-Olkin (Kaiser, 1974)) on the centrality measures. All results are close to unity (CUD: 0.9172, CCDC: 0.9150, DCV: 0.9162, Deceval: 0.8759), indicating that the correlation of these measures is high enough to factor the matrix of correlation coefficients. Following this procedure, we defined the number of components to retain using the scaled Kaiser-Guttman test, which measures the cumulative percentage of explained variance. The first four principal components (PC1, PC2, PC3, and PC4) were selected for all FMIs, given that they surpass the 70% threshold established by that test.

The principal components are linear combinations (i.e., eigenvalues) of the original variables, in this case represented by the centrality measures. Among these linear combinations, the retained components jointly explain a large part of the variance of the centrality measures. For the CUD network, these components explain 94.14% of the centrality measures total variance. Thus, the portion of variance that remains unexplained (i.e., 1 – 0.9414) arises from the fact that these four components do not contain all the information about the centrality in this FMI. The percentage of unexplained variance per measure is presented in the last column of Table 1, and its average value is the same percentage not explained by the components retained (5.86%). The centrality measures with the highest percentage of unexplained variance are hub weighted 22.56%, authority weighted 20.84%, betweenness 18.37%, closeness weighted 14.78%, eccentricity weighted 14.63%, and closeness 11.95%.

Table 1. Principal Component Analysis for CUD

Centrality measure	Components				Unexplained variance
	PC1	PC2	PC3	PC4	
Degree	0.215	0.103	-0.139	-0.071	0.41%
Degree weigthed	0.209	-0.184	0.157	0.024	0.60%
Indegree	0.213	0.101	-0.145	-0.074	2.11%
Indegree weigthed	0.208	-0.183	0.157	0.020	1.85%
Outdegree	0.213	0.104	-0.130	-0.065	2.55%
Outdegree weigthed	0.208	-0.182	0.155	0.028	1.83%
Closeness	0.190	0.253	-0.036	0.132	11.95%
Closeness weigthed	0.040	0.464	0.485	-0.287	14.78%
Betweennes	0.199	-0.023	-0.052	-0.075	18.37%
Eccentricity	0.120	0.214	-0.042	0.912	3.02%
Eccentricity weigthed	0.030	0.468	0.530	0.060	14.63%
Eigenvector	0.214	0.123	-0.144	-0.067	0.86%
Eigenvector weigthed	0.213	-0.148	0.112	0.007	1.48%
Authority	0.207	0.130	-0.162	-0.055	5.35%
Authority weigthed	0.170	-0.232	0.255	0.046	20.84%
Hub	0.206	0.142	-0.139	-0.041	6.43%
Hub weigthed	0.167	-0.234	0.256	0.082	22.56%
PageRank	0.214	0.093	-0.135	-0.073	2.16%
PageRank weigthed	0.211	-0.159	0.125	0.009	2.32%
CheiRank	0.214	0.096	-0.127	-0.069	2.49%
CheiRank weigthed	0.212	-0.150	0.114	0.008	2.31%
Random-walk betweenness	0.211	0.117	-0.129	-0.069	4.04%
SinkRank	0.214	0.089	-0.132	-0.072	2.20%
SinkRank weigthed	0.211	-0.156	0.120	0.007	2.32%
SourceRank	0.214	0.092	-0.123	-0.068	2.43%
SourceRank weigthed	0.212	-0.146	0.108	0.006	2.39%
% of variance explained	**78.31%**	**7.86%**	**5.27%**	**2.70%**	

Notes: authors' calculations

For the CCDC, the components retained jointly explain 91.38% of the total variation of the transactions in this FMI. This result implies that the amount of variation of the centrality measures not explained by these components is 8.62%, which is the same average percentage of unexplained variance. Table 2 reports the abovementioned results, along with the percentage of unexplained variance in the last column. The highest results of that unexplained variance correspond to eccentricity (45.27%), betweenness (33.96%), closeness weighted (19.30%), random-walk betweenness (14.91%), and hub weighted (14.70%).

Table 2. Principal Component Analysis for CCDC

Centrality measure	Components				Unexplained variance
	PC1	PC2	PC3	PC4	
Degree	0.221	0.128	-0.111	-0.030	1.10%
Degree weigthed	0.210	-0.220	0.135	0.023	0.37%
Indegree	0.213	0.118	-0.055	-0.229	4.35%
Indegree weigthed	0.201	-0.210	0.180	-0.235	2.28%
Outdegree	0.212	0.129	-0.162	0.183	4.34%
Outdegree weigthed	0.201	-0.212	0.076	0.288	2.50%
Closeness	0.216	0.152	-0.077	-0.034	3.85%
Closeness weigthed	0.057	0.442	0.444	0.097	19.30%
Betweennes	0.182	0.045	-0.139	0.033	33.96%
Eccentricity	0.151	0.199	-0.043	-0.065	45.27%
Eccentricity weigthed	0.045	0.367	0.660	0.157	13.26%
Eigenvector	0.217	0.155	-0.097	-0.037	2.68%
Eigenvector weigthed	0.211	-0.208	0.126	0.019	1.61%
Authority	0.209	0.129	-0.046	-0.227	7.12%
Authority weigthed	0.177	-0.228	0.243	-0.284	12.82%
Hub	0.207	0.140	-0.148	0.165	8.15%
Hub weigthed	0.175	-0.226	0.117	0.362	14.70%
PageRank	0.213	0.110	-0.059	-0.230	4.72%
PageRank weigthed	0.205	-0.189	0.143	-0.223	3.39%
CheiRank	0.211	0.114	-0.171	0.200	4.62%
CheiRank weigthed	0.205	-0.189	0.043	0.274	2.84%
Random-walk betweenness	0.201	0.156	-0.108	-0.018	14.91%
SinkRank	0.213	0.108	-0.060	-0.232	4.77%
SinkRank weigthed	0.205	-0.187	0.141	-0.227	3.62%
SourceRank	0.212	0.111	-0.171	0.201	4.59%
SourceRank weigthed	0.205	-0.186	0.037	0.280	3.06%
% of variance explained	**73.50%**	**10.62%**	**3.85%**	**3.41%**	

Notes: authors' calculations

The principal components retained for DCV jointly explain 92.24% of the total variation of transactions in this securities depository (Table 3). The first component explains 75.11% while the other components contribute with values below 10%. The average percentage of unexplained variance (7.76%) is mostly concentrated on eccentricity (37.25%), closeness weighted (20.91%), betweenness (18.02%), and hub weighted (15.58%).

Table 3. Principal Component Analysis for DCV

Centrality measure	Components				Unexplained variance
	PC1	PC2	PC3	PC4	
Degree	0.221	0.065	-0.117	-0.090	1.08%
Degree weigthed	0.202	-0.233	0.237	0.004	0.61%
Indegree	0.218	0.062	-0.109	-0.109	4.00%
Indegree weigthed	0.190	-0.228	0.318	-0.184	1.82%
Outdegree	0.218	0.065	-0.122	-0.067	4.30%
Outdegree weigthed	0.199	-0.210	0.077	0.302	3.62%
Closeness	0.198	0.252	0.083	-0.028	8.71%
Closeness weigthed	0.106	0.450	0.275	0.154	20.91%
Betweennes	0.189	0.042	-0.300	-0.057	18.02%
Eccentricity	0.137	0.305	0.200	-0.003	37.25%
Eccentricity weigthed	0.077	0.472	0.419	0.264	9.31%
Eigenvector	0.218	0.106	-0.131	-0.115	1.52%
Eigenvector weigthed	0.209	-0.193	0.195	-0.050	1.25%
Authority	0.215	0.053	-0.045	-0.101	8.24%
Authority weigthed	0.122	-0.192	0.480	-0.562	3.46%
Hub	0.214	0.056	-0.059	-0.056	9.11%
Hub weigthed	0.165	-0.208	0.065	0.485	15.58%
PageRank	0.217	0.064	-0.133	-0.085	4.17%
PageRank weigthed	0.206	-0.164	0.034	0.170	8.04%
CheiRank	0.217	0.063	-0.144	-0.059	4.30%
CheiRank weigthed	0.208	-0.140	-0.006	0.222	7.01%
Random-walk betweenness	0.209	0.123	-0.174	-0.109	6.65%
SinkRank	0.217	0.063	-0.142	-0.084	4.15%
SinkRank weigthed	0.208	-0.154	0.013	0.156	7.68%
SourceRank	0.217	0.065	-0.148	-0.058	4.15%
SourceRank weigthed	0.210	-0.133	-0.020	0.194	6.72%
% of variance explained	**75.11%**	**8.55%**	**5.09%**	**3.49%**	

Notes: authors' calculations

For Deceval, the components retained jointly explain 87.78% of the variance of the securities transactions in this depository (Table 4). The complementary percentage (12.22%) is the average portion of the centrality measures variance that is not explained by this subset of components. The centrality measures least represented by this group are hub weighted (36.12%), authority weighted (29.77%), eccentricity weighted (27.46%), betweenness (25.76%), and eccentricity (25.88%).

Table 4. Principal Component Analysis for Deceval

Centrality measure	Components				Unexplained variance
	PC1	PC2	PC3	PC4	
Degree	0.240	-0.025	-0.197	-0.016	1.00%
Degree weigthed	0.209	-0.058	0.339	-0.047	6.17%
Indegree	0.235	-0.022	-0.186	-0.108	4.20%
Indegree weigthed	0.193	-0.045	0.305	-0.323	6.01%
Outdegree	0.232	-0.028	-0.199	0.096	5.44%
Outdegree weigthed	0.184	-0.057	0.260	0.395	7.56%
Closeness	0.022	0.488	0.082	-0.005	14.41%
Closeness weigthed	0.030	0.504	0.006	0.018	9.69%
Betweennes	0.216	-0.035	-0.005	-0.011	25.76%
Eccentricity	0.100	0.408	0.005	0.023	25.88%
Eccentricity weigthed	0.016	0.453	0.029	0.026	27.46%
Eigenvector	0.243	0.017	-0.129	-0.017	3.15%
Eigenvector weigthed	0.228	-0.025	0.258	0.003	4.56%
Authority	0.222	-0.024	-0.252	-0.097	8.19%
Authority weigthed	0.106	-0.028	0.362	-0.407	29.77%
Hub	0.216	-0.029	-0.257	0.097	11.77%
Hub weigthed	0.087	-0.046	0.264	0.489	36.12%
PageRank	0.234	-0.017	-0.189	-0.110	4.86%
PageRank weigthed	0.211	-0.043	0.144	-0.231	16.66%
CheiRank	0.235	-0.020	-0.137	0.112	6.91%
CheiRank weigthed	0.211	-0.045	0.152	0.268	13.76%
Random-walk betweenness	0.180	0.331	0.021	-0.018	10.40%
SinkRank	0.235	-0.020	-0.176	-0.111	4.52%
SinkRank weigthed	0.214	-0.045	0.146	-0.229	14.57%
SourceRank	0.237	-0.024	-0.132	0.107	6.36%
SourceRank weigthed	0.214	-0.048	0.147	0.256	12.33%
% of variance explained	**60.58%**	**13.46%**	**7.79%**	**5.95%**	

Notes: authors' calculations

The results reported above are used to identify redundant centrality measures for each FMI, given that, these variables are, to a large extent, represented by the first four components. We identify the redundant variables using the first component because it explains the highest degree of co-movement across centrality measures. The scores of this component are standardized (by subtracting the mean and dividing them by the standard deviation) and reorganized in decreasing order so as to easily identify the measures with the lowest contribution. Table 5 presents the results for these centrality measures, whose contribution to the first component is below the average scores of the other measures.

Table 5. Redundant centrality measures

	CUD	CCDC	DCV	Deceval
Indegree weighted			-0.08	
Betweenness		-0.21	-0.10	
Closeness				-2.25
Closeness weigthed	-3.04	-3.09	-2.27	-2.15
Eccentricity	-1.43	-0.94	-1.46	-1.16
Eccentricity weighted	-3.25	-3.39	-3.05	-2.34
Hub weighted	-0.46	-0.39	-0.73	-1.34
Authority weighted	-0.40	-0.33	-1.86	-1.07
Random-walk betweenness				-0.03

Notes: This table presents the centrality measures considered redundant along with their respective rescaled scores that represent their contribution to the index. The lower the value, the lower the contribution of the centrality measure to the general index.

For most FMIs, the redundant measures are closeness weighted, eccentricity (weighted and unweighted), hub weighted, and authority weighted. The closeness measure is given by the inverse of the distance between nodes, and in its weighted form, this measure is defined by the same inverse distance scaled by the total amount of transactions. Thus, either weighted or not, this measure produces the same ranking of the most central institutions and, therefore, can be discarded. Eccentricity centrality, weighted and unweighted, are two additional measures identified as redundant across all FMIs. This finding coincides with the low eigenvalues of these measures in the first component (column PC1 in Tables 1 - 4) but also verifies the fact that PCA rejects the variables associated with the last principal components, as shown in Jollife (1973). Other redundant measures are Hub and Authority in their weighted form, random-walk betweenness (only for Deceval), and betweenness (for CCDC and DCV). According to intuition, the weights used to compute the weighted versions of these measures are more or less the same, either because the amount, the number of transactions or their product generate similar results. Thus, given that these measures do not provide information beyond what their unweighted versions do, they can also be discarded.

5.2. Robustness checks

The redundancy of the centrality measures is corroborated in four ways, using: *i)* subsamples of measures; *ii)* subsamples of system participants, *iii)* a constrained method of data reduction, and *iv)* a clustering method. For the first robustness check we separate the centrality measures according to the direction the nodes point on the networks. One subset includes measures based on links pointing towards the network (i.e., incoming criterion) and the other contains measures with links pointing out of the network (i.e., outgoing criterion). The measures that do not depend on the direction the nodes point (e.g., closeness, betweenness, eccentricity, eigenvector centrality, and random-walk betweenness) are included in both subgroups so as to ensure that our results consider all measures.[15] Table 6 presents the redundant measures for these subsamples in columns (2) and (3). For comparison purposes, the redundant measures identified in the previous section are shown in column (1).

The second robustness check uses two subsamples of system participants: banks and nonbanks, and their redundant measures are reported in columns (4) and (5). The third robustness check is based on the constrained method of data reduction (RDA), previously explained in section 3.2. This parametric approach was implemented in panel data, setting each centrality measure (y) as a function of daily indicators (X) considered the main drivers of transactional activity in each FMI and institution's fixed effects. A description of these explanatory variables along with the results obtained from the first step of this method are presented in Appendix B.[16] The measures identified as redundant using RDA are shown in column (6). Lastly, we study the average-linkage clustering method, previously explained in section 3.3. The redundant measures are presented in column (7) and the corresponding dendrograms (i.e., cluster trees) are shown in Appendix C.

[15] The subgroup representing the incoming criterion includes sixteen measures: in-degree (weighted and unweighted), closeness (weighted and unweighted), betweenness, eccentricity (weighted and unweighted), eigenvector centrality (weighted and unweighted), authority (weighted and unweighted), page-rank (weighted and unweighted), random-walk betweenness, and sink-rank (weighted and unweighted). The subgroup for the outgoing criterion also includes sixteen measures: out-degree (weighted and unweighted), closeness (weighted and unweighted), betweenness, eccentricity (weighted and unweighted), eigenvector centrality (weighted and unweighted), hub (weighted and unweighted), chei-rank (weighted and unweighted), random-walk betweenness, and source rank (weighted and unweighted).

[16] Other variables that may influence the centrality measures are related to the institution balances that have a monthly frequency, and therefore they are not included as explanatory variables in the implementation of RDA.

Table 6. Robustness checks

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	PCA	**PCA**	**PCA**	**PCA**	**PCA**	**RDA**	**Clustering**
	All measures	Incoming criterion	Outgoing criterion	Banks	Non-banks	All measures	All measures
CUD							
Betweenness							X
Closeness					-0.20		X
Closeness weigthed	**-3.04**	-2.35	-2.35	-2.90	-3.13	-3.58	X
Eccentricity	**-1.43**	-0.96	-0.96	-1.42	-1.53	-0.01	X
Eccentricity weighted	**-3.25**	-2.51	-2.51	-3.35	-3.05	-3.23	X
Hub weighted	**-0.46**		-0.25	-0.60	-0.42	-0.33	X
Authority weighted	**-0.40**	-0.20		-0.48	-0.48	-0.09	X
CCDC							
Betweenness	**-0.21**	-0.07	-0.01	-0.20	-0.28	-0.06	X
Closeness weigthed	**-3.09**	-2.35	-2.35	-3.10	-3.07	-3.52	X
Eccentricity	**-0.94**	-0.60	-0.60	-0.77	-1.19		X
Eccentricity weighted	**-3.39**	-2.62	-2.62	-3.45	-3.32	-3.26	X
Hub weighted	**-0.39**		-0.18	-0.35	-0.38	-0.30	X
Authority weighted	**-0.33**	-0.13		-0.28	-0.21		X
DCV							
Indegree weighted	**-0.08**			-0.23		-0.02	
Betweenness	**-0.10**			-0.06		-0.21	X
Closeness					-0.05		X
Closeness weigthed	**-2.27**	-1.70	-1.89	-1.76	-2.48	-2.22	X
Eccentricity	**-1.46**	-0.96	-1.13	-1.74	-1.36	-0.16	X
Eccentricity weighted	**-3.05**	-2.38	-2.60	-2.71	-3.17	-3.91	X
Hub weighted	**-0.73**		-0.65	-1.06	-0.27	-0.13	X
Authority weighted	**-1.86**	-1.47		-2.30	-1.79	-1.44	X
Deceval							
Indegree weighted				-0.15			
Betweenness				-1.12			
Closeness	**-2.25**	-1.78	-1.77	-1.82	-2.32	-2.77	X
Closeness weigthed	**-2.15**	-1.71	-1.68	-1.87	-2.21	-2.43	X
Eccentricity	**-1.16**	-0.83	-0.78	-1.22	-1.10	-0.07	
Eccentricity weighted	**-2.34**	-1.93	-1.88	-1.81	-2.42	-2.86	
Hub weighted	**-1.34**		-0.95	-0.39	-1.05	-0.34	X
Authority weighted	**-1.07**	-0.77		-1.09	-1.17	-0.30	X
Random-walk betw.	**-0.03**			-1.25			

Notes: This table presents the centrality measures considered redundant along with their respective rescaled scores that represent their contribution to the index. The lower the value, the lower the contribution to the general index. For the clustering method, the variables identified with an X are considered redundant as they exhibit the highest average Euclidean distance to the other centrality measures.

Most of the redundant measures remain almost unchanged, even considering reduced data sets, a model-based approach, and a clustering method. As expected, these measures change a bit when subsamples of data are considered (see columns 2 and 3) because there is a loss of information caused by not evaluating the entire set of measures. This does not occur when we split the sample of system participants into banks and nonbanks or when we use RDA. Indeed, the results obtained from this model-based method are qualitatively almost the same as those obtained with PCA. The same occurs from applying the selected clustering method. In all FMIs, the last variables to join the main groups in dendrograms are the same variables identified as redundant with the other statistical methods. Indeed, these measures exhibit the highest average Euclidean distance towards the other centrality measures, as can be seen in Table C.1 in Appendix C. Hence, we can be confident that the centrality measures identified as redundant with PCA are roughly the same under other criteria. These variables are eccentricity and eccentricity weighted, closeness weighted, hub weighted, and authority weighted. As the presented methods suggest, these variables barely contribute to determine centrality and, therefore, can be consistently discarded from the general indices. The number of variables retained for the construction of the general centrality indices are twenty-one for CUD, twenty for CCDC, and nineteen for DCV and Deceval. These indices are obtained from the first principal component.

5.3. Centrality indices for financial market infrastructures

The composite indices of centrality obtained for each FMI are synthetic measures that cover several definitions and, therefore, are more powerful than the individual centrality criteria to identify the participants that can affect the stability in the network, either entering or leaving the ranking of institutions with the greatest centrality. Table 7 presents the Top-10 of the most central participants obtained from the full sample of measures and financial institutions, ranked in descending order by the score obtained in the index (i.e., average score for the period of study, weighted by the scores obtained from PCA). Due to statistical reserve, the names of these institutions are undisclosed.

The results for the CUD, presented in columns (1) and (2), identify eight banks (B), one brokerage firm (BF), and one mutual fund (MF) as the most central financial institutions. In the first five positions appear the participants that most contribute with payments in value and number of transactions. A salient feature of this ranking is the considerable distance in the scores obtained by the banks in the first and second positions, which suggests that the bank B9 is to a large extent the most central participant in the system.

Table 7. Top-10 of the most central participants

CUD		CCDC		DCV		Deceval	
(1) System participant	(2) Score in the index	(3) System participant	(4) Score in the index	(5) System participant	(6) Score in the index	(7) System participant	(8) Score in the index
B9	21.97	B15	7.84	BF30	13.10	BF30	12.21
B53	15.34	B9	6.22	B9	10.23	BF64	9.64
B15	12.37	B25	5.59	B15	9.60	BF16	8.40
B3	12.19	BF05	4.98	B21	8.20	BF53	7.91
BF30	10.32	BF30	4.69	B11	7.60	BF28	7.82
B14	9.78	FC13	4.44	B3	7.26	BF24	5.06
B21	9.46	B3	3.77	B53	7.13	BF78	4.12
B25	9.40	B11	2.96	FC13	6.58	BF05	4.06
B8	8.76	BF78	2.69	B42	5.53	BF99	3.33
MF26	8.40	FC43	2.48	FC43	5.29	BF5006	2.20

Notes: authors' calculations. The letter B is used to identify banks, BF for brokerage firms, MF for mutual funds, and FC for financial corporations.

In CCDC the participants with the highest centrality scores are five banks, three brokerage firms, and two financial corporations (columns (3) and (4)). The banks in the first three positions are the most active participants in the peso/dollar market. However, the differences in the scores they achieved are small, indicating that the second and third participants are not far from the bank in the first position. Similar small differences are observed in the remaining places, which suggest that monitoring activities on this FMI should make emphasis on all the financial institutions in this ranking.

For the central securities depository for sovereign debt securities (DCV), the most central participants are seven banks, one brokerage firm, and two financial corporations. These results, reported in columns (5) and (6), reveal that the participants in the Top-3 positions are very close to one another, and therefore, they should be closely monitored. Columns (7) and (8) report the results for Deceval, where the top ten positions are occupied by brokerage firms. As in DCV, the most central participant is the brokerage firm BF30 and the score it obtains is very far from the participant in the second position. Hence, it can be said that for the period of study, this brokerage firm was very active in carrying out transactions, either using as collateral sovereign debt, equities, bonds, or term deposits certificates. When comparing the results between networks, it can be seen that the most central participants in

CCDC, DCV, and Deceval also appear in the ranking of CUD. This result can be attributed to the fact that the cash leg of the transactions in these FMIs are settled in CUD.

The stability of the ranking can be considered a useful tool to monitor these financial market infrastructures, in the sense that any change in the institutions identified as the most central, or in the top positions can give signals to monitor systems participants in a closer way. In such cases, a more detailed inspection of the factors driving these changes will be required so as to determine the causes and expected consequences in the network (FMI) under study. Thus, monitoring activities should be geared towards studying day-to-day changes in the financial performance of the financial institutions participating in these FMIs.

Conclusions

The concept of centrality is commonly used to identify the participants that play the most relevant role in systems with a network structure, which is key for monitoring purposes. The wide variety of centrality measures can make monitoring all financial institutions under all criteria a great challenge for the network analyst, especially when the number of system's participants is considerably large. We use PCA to reduce the information extracted from twenty-six centrality measures applied on transactions data of four FMIs (the large-value payment system (CUD), the foreign exchange clearing house (CCDC) and two securities depositories —DCV and Deceval—). In those systems, the measures mostly identified as redundant are closeness weighted, authority weighted, hub weighted, eccentricity, and eccentricity weighted. As these measures are, to a large extent, contained in linear combinations of other centrality measures represented by the retained components, they can be discarded from the general indices of centrality. These indices facilitate the monitoring activities to these FMIs, as they reduce the complexity of the data set by eliminating the redundant information shared by the original variables.

References

Baek, S., Soramäki, K., and Yoon, J. (2014). "Network indicators for monitoring intraday liquidity in BOK-Wire+", *Journal of Financial Market Infrastructures*, 2 (3), 37-66.

Banco de la República. (2020). Payment System Report, June.

Batool, K., and Niazi, M. (2014). Towards a Methodology for Validation of Centrality Measures in Complex Networks, PLoS ONE, 9 (4).

Barrat, A., Barthélemy, M., Pastor-Satorras, R., and Vespignani, A. (2004). "The architecture of complex weighted networks". Proceedings of the National Academy of Sciences of the United States of America.

Battiston, S., Puliga, M., Kaushik, R., Tasca, P., and Caldarelli, G. (2012). "DebtRank: Too central to fail?", Financial Networks, the FED and systemic risk. Scientific Reports, 2.

Battiston, S., Caldarelli, G., D'Ericco, M., Gurciullo, S. (2016). "Leveraging the network: a stress-test framework based on DebtRank", Statistics and Risk Modelling, 33(3-4), 117–138.

Bavelas, A. (1950). Communication patterns in task-oriented groups. *Journal of the Acoustical Society of America*, 22, 725–730.

Bech, M., Hancock, J., Rice, T., and Wadsworth, A. (2020). "On the future of securities settlement", BIS Quarterly Review, March.

Bedford, P., Millard, S., and Yang, J. (2005). "Analysing the impact of operational incidents in large-value payment systems: A simulation approach", in Leinonen, H (ed), Liquidity, risks and speed in payment and settlement systems: a simulation approach, Bank of Finland.

BIS-PFMI. (2012). Principles for financial market infrastructures.

BIS-CPSS. (2003). A glossary of terms used in payments and settlement systems. March.

Bollerslev, T., and Melvin, M. (1994). "Bid-ask spreads and volatility in the foreign exchange market: An empirical analysis", *Journal of International Economics*, Vol 36, 355-372.

Bonacich, P., and Lloyd, P. (2001). Eigenvector-like measures of centrality for asymmetric relations. *Social Networks*, 23, 191-201.

Brin, S., and Page, L. (1998). The anatomy of large-scale hyper-textual Web search engine, *Computer Networks and ISDN*, 30, 107-117.

Chepelianskii, A. (2010). Towards physical laws of software architecture, arXiv:1003.545

Dungey, M., Luciani, M., and Veredas, D. (2014). "Googling SIFIs", Centre for International Finance and Regulation, Working Paper 003/2013.

Goldbeck, J. (2013). Analyzing the social web. Elsevier

Hage, P., and Harary, F. (1995). Eccentricity and Centrality in Networks, *Social Networks*, 17 (1), 57-63.

Hirschman, A. (1945). National Power and the Structure of Foreign Trade, University of California Press, Berkley.

Hotelling, H. (1933). Analysis of Complex Statistical Variables into Principal Components, *Journal of Education Phycology,* 24, 417-441.

Israëls, A. (1986). Interpretation of Redundancy Analysis: rotated vs unrotated solutions, *Applied Stochastic Models and Data Analysis*, 2, 121-130.

Isräels, A. (1992). Redundancy Analysis for various types of variables, *Statistica Applicata* 4 (4), 531-542.

Joliffe, IT. (1972). "Discarding variables in a principal components analysis I: Artificial Data", Applied Statistics, 22 (2), 160-173.

Joliffe, IT. (1973). "Discarding variables in a principal components analysis II: Real data", Applied Statistics, 22 (1), 21-31.

Kaiser, H. (1960). The application of electronic computers to factor analysis, *Education and Phycological Measurement*, 20, 141-151.

Kaiser, H.F. (1974). "An index of factorial simplicity", Phsychometrika 39, 31-36.

Kelley, T. (1940). Talents and tasks: their conjunction in a democracy for wholesome living and national defense. Harvard Education Press no.1, Graduate School of Education, Harvard University.

Kleinberg, J. (1999). Authoritative sources in a hyperlinked environment, *Journal of the ACM*, 46 (5), 604–632.

León, C., Mariño, R., and Cadena, C. (2021). "Do central counterparties reduce counterparty and liquidity risk? Empirical evidence", *Algorithmic Finance*, 9, 25-34.

Newman, M. (2005). A measure of betweenness centrality based on random walks, *Social networks*, 27 (1), 39-54.

Newman, M. (2006). Finding community structure in networks using eigenvectors of matrices, *Phys Rev E,* 74 (3). [DOI: 10.1103/PhysRevE.74.036104]

Newman, M. (2008). The mathematics of networks. In: Blume L, editor. SD, editors, The New Palgrave Encyclopedia of Economics. Basingstoke: Palgrave Macmillan. 2nd edition.

Pearson, K. (1901). On Lines and Planes of Closest Fit to Systems of Points in Space, *Philosophical Magazine*, 2 (11), 559-572.

Pozzi, F., Fersini, E., Messin, E., and Liu, B. (2017). Sentiment Analysis in Social Networks. Elsevier.

Rao, C.R. (1964). The Use and Interpretation of Principal Components Analysis in Applied Research, *Sankhyā: The Indian Journal of Statistics*, 26 (4), 329-358.

Rovira, P., and Spelta, A. (2019). "Identifying systemically important financial institutions", Computational Management Science, 16, 155-185.

Sarno, L., and Taylor, M. (2001). The Microstructure of Foreign Exchange Market: A Selective Survey of the Literature. Princeton Studies in International Economics, 89, May.

Soramäki, K., and Cook, S. (2013). SinkRank: An Algorithm for Identifying Systemically Important Banks in Payment Systems, *Open-Assessment E-Journal*, 7, 2013-2028.

Temizsoy, A., Iori, G., and Montes-Rojas, G. (2017). Network centrality and funding rates in the e-MID interbank market, *Journal of Financial Stability*, 33, 346-365.

van den Wollenberg, A. (1977). Redundancy Analysis - An alternative for canonical analysis, *Psychometrika,* 42 (2), 207-219.

Wang, G., and Yau, J. (2000). Trading volume, bid–ask spread, and price volatility in futures markets. *The Journal of Futures Markets*, 20 (10), 943-970.

White, S., and Smith, P. (2003). Algorithms for estimating relative importance in networks. ACM SIGKDD International Conference on Knowledge Discovery and Data Mining.

Appendix A.

Table A.1 Summary statistics of the centrality measures

	Panel A: CUD			Panel B: CCDC			Panel C: DCV			Panel D: Deceval		
Variable	Obs	Mean	S.D.	Obs	Mean	S.D.	Obs	Mean	S.D.	Obs	Mean	S.D.
Degree	46,303	0.009	0.010	12,939	0.030	0.018	24,135	0.017	0.019	18,999	0.021	0.026
Degree weigthed	46,303	0.009	0.019	12,939	0.031	0.030	24,135	0.017	0.029	18,999	0.021	0.033
Indegree	46,303	0.009	0.010	12,939	0.031	0.019	24,135	0.017	0.019	18,999	0.021	0.030
Indegree weigthed	46,303	0.009	0.020	12,939	0.031	0.032	24,135	0.017	0.031	18,999	0.021	0.042
Outdegree	46,303	0.009	0.010	12,939	0.031	0.018	24,135	0.017	0.019	18,999	0.021	0.024
Outdegree weigthed	46,303	0.009	0.019	12,939	0.031	0.031	24,135	0.017	0.031	18,999	0.021	0.032
Closeness	46,066	0.009	0.001	12,939	0.031	0.005	23,812	0.017	0.003	18,999	0.021	0.041
Closeness weigthed	46,066	0.009	0.002	12,939	0.031	0.006	23,812	0.017	0.006	18,999	0.021	0.036
Betweennes	46,303	0.009	0.022	12,911	0.031	0.041	24,135	0.017	0.036	18,984	0.021	0.051
Eccentricity	46,303	0.009	0.001	12,939	0.031	0.005	24,135	0.017	0.003	18,999	0.021	0.007
Eccentricity weigthed	46,299	0.009	0.001	12,939	0.031	0.004	24,135	0.017	0.007	18,999	0.021	0.022
Eigenvector	46,303	0.009	0.008	12,939	0.031	0.013	24,135	0.017	0.015	18,999	0.021	0.020
Eigenvector weigthed	46,303	0.009	0.015	12,939	0.031	0.025	24,135	0.017	0.023	18,999	0.021	0.025
Authority	46,303	0.009	0.009	12,939	0.031	0.018	24,135	0.017	0.017	18,999	0.021	0.028
Authority weigthed	46,303	0.009	0.026	12,939	0.031	0.038	24,135	0.017	0.045	18,999	0.021	0.075
Hub	46,303	0.009	0.008	12,939	0.031	0.017	24,135	0.017	0.018	18,999	0.021	0.023
Hub weigthed	46,303	0.009	0.026	12,939	0.031	0.037	24,135	0.017	0.037	18,999	0.021	0.063
PageRank	46,303	0.009	0.009	12,939	0.031	0.016	24,135	0.017	0.016	18,999	0.021	0.023
PageRank weigthed	46,303	0.009	0.016	12,939	0.031	0.026	24,135	0.017	0.024	18,999	0.021	0.028
CheiRank	46,303	0.009	0.008	12,939	0.031	0.016	24,135	0.016	0.014	18,999	0.021	0.018
CheiRank weigthed	46,303	0.009	0.015	12,939	0.031	0.026	24,135	0.014	0.016	18,999	0.021	0.020
Random-walk betw.	46,303	0.009	0.006	12,939	0.031	0.009	24,135	0.017	0.012	18,999	0.021	0.021
SinkRank	46,303	0.009	0.009	12,939	0.031	0.017	24,135	0.017	0.017	18,999	0.021	0.024
SinkRank weigthed	46,303	0.009	0.016	12,939	0.031	0.027	24,135	0.017	0.024	18,999	0.021	0.028
SourceRank	46,303	0.009	0.009	12,939	0.031	0.016	24,135	0.017	0.016	18,999	0.021	0.019
SourceRank weigthed	46,303	0.009	0.015	12,939	0.031	0.026	24,135	0.017	0.019	18,999	0.021	0.021

Notes: Obs. denotes the number of observations and S.D. the standard deviation.

Appendix B.

In absence of theoretical models that identify the core determinants of activity in these FMIs, we resort to the analyst intuition to evaluate daily explanatory variables related to these systems so as to implement RDA. Some of these explanatory variables are constructed at the level of the system's participant while others at the FMI's level.[17]

For CUD, we use as explanatory variables the financial institution's opening balance, the financial institution's share in daily transactions, the Herfindahl-Hirschman index of the total value of transactions (HHI), and the upper bound (i.e., maximum amount of liquidity a system participant (e.g., bank) needs to settle all its payments immediately).[18] The HHI is

[17] Balance sheet data have a monthly frequency, and therefore cannot be used as explanatory variables.
[18] See Bedford, Millard, and Yang (2005) for a more complete explanation on the upper bound.

given by the sum of squared shares ($HHI = \sum_{i=1}^{N}(s_i)^2$ —see Hirschman (1945)), in this case defined by the daily value of transactions. This concentration index is a common variable to all system's participants and therefore it captures system's factors that may affect the centrality results. Two of these variables, the opening balance and the upper bound, pertain to the monitoring tools that according to the BCBS-CPSS (2013) should apply to all banks.[19]

The robustness checks for CCDC are conditioned to assuming as explanatory variables the bid-ask spread, the financial institution's share in multilateral net value, and two market concentration indices (i.e., one for the sold and one for the bought amounts of peso/dollar transactions (HHI gross buy and HHI gross sell)).[20] The bid-ask spread is constructed for each system's participant and is, by definition, related to the microstructure of the foreign exchange market (Wang and Yau, 2000). The bid-ask spread of the foreign exchange market is considered as a standard measure of transaction costs (see Bollerslev and Melvin 1994). As this spread is partially determined by the underlying uncertainty of exchange rate movements (Sarno and Taylor, 2001), the percent changes in the representative market rate is discarded as an explanatory variable. The bid-ask spread is included in model's estimation with a one-day lag and, therefore, partially represents the effects of expectations in the foreign exchange market that may arise from previous trading decisions of financial institutions. A wider spread may allow them to find more easily counterparties willing to close their positions on trading systems. The lagged value of that variable also allows to avoid possible endogeneity problems with the centrality measures that may arise from the fact that this spread, computed as the difference between the max and min quotations, can also be related to the total value of daily transactions. The financial institution's share in multilateral net value is included to capture the peso/dollar transactions carried out for the purpose of obtaining or granting liquidity. The former case (i.e., obtaining liquidity) is observed when this value is positive while the latter when it is negative.

The implementation of RDA for both, DCV and Deceval is set as a function of a turnover ratio given by the value of deliveries relative to the value of securities held (see Bech,

[19] Other variables are total payments and time specific obligations.

[20] Other factors that may affect this market are the participant's expectations on exchange rates and the order flows of transactions. The lack of data related to these factors impeded us to develop a more comprehensive estimation of this market.

Hancock, Rice, and Wadsworth, 2020), financial institution's share in daily transactions, and concentration indices (HHI) constructed for each collateral type used in securities transactions. In the case of DCV, the Herfindahl-Hirschman index was constructed for the value of sovereign debt (TES) used in sell/buy-backs and repo transactions. In the case of Deceval, concentration indices were constructed for bonds, term deposits certificates, and equities. Note that in Deceval, sell/buy-backs can be secured with bonds and term deposits certificates, while repos are mostly collateralized with equities and, to a lesser extent, with bonds. Alternative robustness checks were conducted setting each centrality measure as a function of concentration indices (HHI) based on the value of transactions with sell/buy-backs and repo —both from the buyer's side—, and the results remain almost the same. Table B.1 presents further details on the data sources and description of these explanatory variables.

All panel data models used in RDA's first stage additionally include financial institution's fixed effects to control for the average differences over time that are not captured by the explanatory variables. In cases where not enough further information was included at the system's participant level, these fixed effects play a much more relevant role, as is the case in DCV. Panel data results for each FMI are reported in tables B.2, B.3, B.4, and B.5. The predicted values from this first stage are used as input variables in RDA's second stage.

Table B.1 Description of explanatory variables used in RDA

		Description	Indicator constructed using
CUD	Opening balance	Natural logarithm of the institution's balance at the beginning of the day.	CUD data.
	Transactions share	Financial institution’s share in daily transactions.	CUD data.
	HHI	Sum of squared market shares (of transactions).	CUD data.
	Upper bound	Maximum net debit position.	CUD data.
CCDC	Bid-ask spread	Difference between the maximum and minimum quotations for US dollars per day (in logs).	CCDC data.
	Transactions share	Participant's share in multilateral net value of peso/dollar transactions.	CCDC data.
	HHI gross buy	Constructed for the sold amounts of peso/dollar transactions (gross values of foreign exch. transactions).	CCDC data.
	HHI gross sell	Constructed for the bought amounts of peso/dollar transactions (gross values of foreign exch. transactions).	CCDC data.
DCV	Turnover ratio	The value of deliveries relative to the value of securities held is computed as the ratio between the purchase and sales of securities over the institution's initial balance.	DCV data.
	Transactions share	Financial institution’s share in daily transactions.	DCV data.
	HHI_TES	Sum of squared institution's share in the total value of sovereign debt (TES).	DCV data.
Deceval	Turnover ratio	The value of deliveries relative to the value of securities held is computed as the ratio between the purchase and sales of securities over the institution's initial balance.	Deceval data.
	Transactions share (TDC)	Financial institution’s share in daily transactions on term deposits certificates.	Deceval data.
	Transactions share (Bonds)	Financial institution’s share in daily transactions of corporate non-sovereign bonds.	Deceval data.
	Transactions share (Equities)	Financial institution’s share in daily transactions on equities.	Deceval data.
	HHI_term deposits	Sum of squared institution's share in the total term deposit market value.	Deceval data.
	HHI_bonds	Sum of squared institution's share in the total bonds market value.	Deceval data.
	HHI_equities	Sum of squared institution's share in the total equities market value.	Deceval data.

Notes: authors’ design.

Table B.2 First stage of RDA for CUD

	Initial balance$_t$	Transactions share$_t$	HHI (transactions)$_t$	Upper bound$_t$	R^2-Adj
Degree$_t$	-0.000011 (0.00001)*	0.0318 (0.00186)***	0.0018 (0.00144)	0.000015 (0.000003)***	0.980
Degree weigthed$_t$	-0.000044 (0.00001)***	0.9003 (0.00651)***	0.0007 (0.00221)	-0.000061 (0.000003)***	0.988
Indegree$_t$	-0.000007 (0.00001)	0.0339 (0.00242)***	0.0006 (0.00183)	0.000001 (0.000003)	0.970
Indegree weigthed$_t$	-0.000090 (0.00001)***	0.7966 (0.01366)***	0.0013 (0.00462)	-0.000124 (0.00001)***	0.953
Outdegree$_t$	-0.000015 (0.00001)**	0.0029 (0.00210)***	0.0029 (0.00162)*	0.000028 (0.000003)***	0.970
Outdegree weigthed$_t$	0.000001 (0.000001)	1.0004 (0.00008)***	-0.00001 (0.00005)	0.000000 (0.000001)***	0.990
Closeness$_t$	-0.000001 (0.000002)	0.0027 (0.00045)***	0.0033 (0.00040)***	-0.000014 (0.000001)***	0.819
Closeness weigthed$_t$	0.000005 (0.000009)	-0.0014 (0.00074)*	0.0069 (0.00129)***	-0.000078 (0.000004)***	0.335
Betweennes$_t$	-0.000019 (0.000015)	0.0700 (0.00900)***	-0.0038 (0.00470)	0.000002 (0.00001)	0.955
Eccentricity$_t$	0.000007 (0.000004)	0.0049 (0.00107)***	0.0032 (0.00090)***	-0.000012 (0.000002)***	0.338
Eccentricity weigthed$_t$	0.000006 (0.000002)***	0.0000 (0.00025)	0.0032 (0.00038)***	-0.000015 (0.000001)***	0.114
Eigenvector$_t$	0.020082 (0.00001)***	0.0201 (0.00156)***	0.0026 (0.00128)**	0.000010 (0.000002)***	0.975
Eigenvector weigthed$_t$	-0.000014 (0.00001)***	0.5784 (0.00601)***	-0.0002 (0.00186)	-0.000037 (0.000003)***	0.985
Authority$_t$	-0.000009 (0.00001)	0.0297 (0.00193)***	0.0002 (0.00171)	0.0000003 (0.000004)	0.962
Authority weigthed$_t$	-0.000321 (0.00005)***	1.3824 (0.05003)***	-0.0046 (0.01406)	-0.000172 (0.00002)***	0.723
Hub$_t$	-0.000020 (0.00001)***	0.0246 (0.00156)***	0.0064 (0.00149)***	0.000019 (0.000003)***	0.959
Hub weigthed$_t$	-0.000036 (0.00004)	1.8284 (0.03923)***	0.0011 (0.01120)	0.000025 (0.00001)*	0.802
PageRank$_t$	0.000001 (0.00001)	0.0292 (0.00214)***	0.0011 (0.00158)	-0.000002 (0.000003)	0.967
PageRank weigthed$_t$	-0.000068 (0.00001)***	0.5488 (0.01038)***	0.0004 (0.00359)	-0.000083 (0.000004)***	0.956
CheiRank$_t$	-0.000015 (0.00001)**	0.0271 (0.00221)***	0.0011 (0.00154)	0.000028 (0.000003)***	0.965
CheiRank weigthed$_t$	-0.000008 (0.00001)	0.6407 (0.00510)***	-0.0011 (0.00177)	0.000004 (0.000002)**	0.990
Random-walk betw.$_t$	-0.000001 (0.00001)	0.0149 (0.00173)***	0.0032 (0.00146)**	-0.000015 (0.00001)	0.917
SinkRank$_t$	-0.000002 (0.00001)	0.0299 (0.00224)***	0.0012 (0.00161)	-0.000002 (0.000003)	0.967
SinkRank weigthed$_t$	-0.000065 (0.00001)***	0.5357 (0.01002)***	0.0002 (0.00346)	-0.000078 (0.000004)***	0.958
SourceRank$_t$	-0.000015 (0.00001)**	0.0283 (0.00234)***	0.0012 (0.00158)	0.000027 (0.000003)***	0.964
SourceRank weigthed$_t$	-0.000007 (0.00001)	0.6217 (0.00507)***	-0.0011 (0.00176)	0.000006 (0.000002)***	0.989

Notes: panel-data models with institution fixed effects. Every row presents the results for the model specified for each measure of centrality y_t: y_t = Initial_balance$_t$ + Transactions share$_t$ + HHI_(transactions)$_t$ + Upper_bound$_t$ + ε_t. Estimated parameters are reported on the right-hand side of each column and robust standard errors in parentheses at the left-hand side. Statistical significance at the 1% (***), 5% (**), and 10% (*) levels. The sample period is January 2, 2019, through August 31, 2020. RDA's application to the CUD involves a loss of information of 23.8% (the number of observations drops from 46,066 to 35,063).

Table B.3 First stage of RDA for CCDC

	Bid-ask spread$_{t-1}$	Transactions share$_t$	HHI (gross buy)$_t$	HHI (gross sell)$_t$	R^2-Adj
Degree$_t$	0.0012 (0.00011)***	0.0081 (0.00145)***	0.0128 (0.01325)	-0.0003 (0.01578)	0.814
Degree weigthed$_t$	0.0015 (0.00022)***	0.0822 (0.00436)***	0.0037 (0.02912)	-0.0023 (0.03336)	0.740
Indegree$_t$	0.0011 (0.00013)***	-0.0134 (0.00186)***	0.0132 (0.01660)	-0.0033 (0.01929)	0.767
Indegree weigthed$_t$	0.0015 (0.00025)***	-0.0365 (0.00555)***	-0.0131 (0.03716)	0.0042 (0.04109)	0.669
Outdegree$_t$	0.0013 (0.00013)***	0.0298 (0.00195)***	0.0124 (0.01495)	0.0027 (0.01835)	0.742
Outdegree weigthed$_t$	0.0014 (0.00021)***	0.2023 (0.00469)***	0.0206 (0.02714)	-0.0088 (0.03321)	0.765
Closeness$_t$	0.0003 (0.00003)***	0.0018 (0.00045)***	0.0194 (0.00404)***	0.0131 (0.00462)***	0.801
Closeness weigthed$_t$	0.0002 (0.00006)***	-0.0018 (0.00072)***	0.0270 (0.00690)***	0.0192 (0.00814)***	0.420
Betweennes$_t$	0.0018 (0.00036)***	0.0121 (0.00601)**	-0.0023 (0.00459)	-0.0018 (0.05224)	0.609
Eccentricity$_t$	0.0002 (0.00006)***	0.0017 (0.00072)***	0.0204 (0.00715)***	0.0137 (0.00827)*	0.379
Eccentricity weigthed$_t$	0.0001 (0.00006)	-0.0014 (0.00074)*	0.0225 (0.00642)***	0.0179 (0.00725)***	0.158
Eigenvector$_t$	0.0008 (0.00008)***	0.0048 (0.00110)***	0.0165 (0.00999)*	0.0045 (0.01209)	0.801
Eigenvector weigthed$_t$	0.0011 (0.00017)***	0.0661 (0.00324)***	0.0064 (0.02276)	0.0018 (0.02601)	0.758
Authority$_t$	0.0010 (0.00012)***	-0.0108 (0.00168)***	0.0151 (0.01579)	-0.0033 (0.01810)	0.765
Authority weigthed$_t$	0.0016 (0.00034)***	-0.0593 (0.00788)***	-0.0196 (0.04904)	0.0075 (0.05713)	0.538
Hub$_t$	0.0012 (0.00012)***	0.0258 (0.00164)***	0.0129 (0.01362)	0.0041 (0.01681)	0.742
Hub weigthed$_t$	0.0010 (0.00028)***	0.2814 (0.00911)***	0.0356 (0.03808)	-0.0154 (0.04622)	0.671
PageRank$_t$	0.0010 (0.00012)***	-0.0113 (0.00172)***	0.0136 (0.01504)	-0.0007 (0.01783)	0.746
PageRank weigthed$_t$	0.0013 (0.00021)***	-0.0215 (0.00454)***	-0.0049 (0.03027)	0.0049 (0.03315)	0.668
CheiRank$_t$	0.0011 (0.00012)***	0.0268 (0.00186)***	0.0135 (0.01452)	0.0053 (0.01731)	0.717
CheiRank weigthed$_t$	0.0013 (0.00018)***	0.1451 (0.00359)***	0.0160 (0.02336)	-0.0026 (0.02882)	0.742
Random-walk betw.$_t$	0.0004 (0.00007)***	0.0024 (0.00102)***	0.0207 (0.00864)***	0.0118 (0.01016)	0.652
SinkRank$_t$	0.0010 (0.00012)***	-0.0120 (0.00180)***	0.0121 (0.01556)	0.0003 (0.01844)	0.744
SinkRank weigthed$_t$	0.0013 (0.00021)***	-0.0258 (0.00462)***	-0.0058 (0.03142)	0.0050 (0.03404)	0.665
SourceRank$_t$	0.0011 (0.00012)***	0.0280 (0.00196)***	0.0117 (0.01489)	0.0057 (0.01777)	0.718
SourceRank weigthed$_t$	0.0013 (0.00019)***	0.1464 (0.00372)***	0.0129 (0.02354)	-0.0011 (0.02915)	0.739

Notes: panel-data models with institution fixed effects. Every row presents the results for the model specified for each centrality measure y_t: y_t = Bid-ask_spread$_{t-1}$ + Transactions share$_t$ + HHI(gross buy)$_t$ + HHI(gross sell)$_t$ + ε_t. Estimated parameters are reported on the right-hand side of each column and robust standard errors in parentheses at the left-hand side. Statistical significance at the 1% (***), 5% (**), and 10% (*) levels. The sample period is January 2, 2019, through August 31, 2020. RDA's application to the CCDC involves a loss of information of 28.4% (the number of observations drops from 12,911 to 9,238).

Table B.4 First stage of RDA for DCV

	Turnover ratio$_t$	Transactions share$_t$	HHI (sovereign debt)$_t$	R^2-Adj
Degree$_t$	0.00020 (0.00013)	0.079 (0.01458)***	0.008 (0.00245)***	0.930
Degree weigthed$_t$	0.00019 (0.00014)	-0.514 (0.05541)***	0.001 (0.00544)	0.820
Indegree$_t$	0.00015 (0.00014)	0.032 (0.01889)*	0.008 (0.00277)***	0.905
Indegree weigthed$_t$	0.00016 (0.00012)	-1.227 (0.06843)***	-0.002 (0.00658)	0.770
Outdegree$_t$	0.00025 (0.00013)**	0.129 (0.01891)***	0.009 (0.00299)***	0.899
Outdegree weigthed$_t$	0.00023 (0.00018)	0.520 (0.06372)***	0.005 (0.00723)	0.777
Closeness$_t$	-0.00003 (0.00003)	0.009 (0.00514)*	0.031 (0.00111)***	0.751
Closeness weigthed$_t$	-0.00006 (0.00005)	0.015 (0.00874)*	0.029 (0.00193)***	0.515
Betweennes$_t$	0.00031 (0.00025)	0.233 (0.05031)***	0.002 (0.00779)	0.804
Eccentricity$_t$	-0.00004 (0.25982)	-0.015 (0.00729)**	0.032 (0.00141)***	0.341
Eccentricity weigthed$_t$	-0.00006 (0.0004)	0.011 (0.00671)*	0.033 (0.00192)***	0.035
Eigenvector$_t$	0.00015 (0.00009)*	0.040 (0.01231)***	0.014 (0.00209)***	0.911
Eigenvector weigthed$_t$	0.00015 (0.00010)	-0.466 (0.03801)***	0.007 (0.00397)*	0.842
Authority$_t$	0.00011 (0.00012)	0.027 (0.01691)	0.009 (0.00260)***	0.901
Authority weigthed$_t$	0.00008 (0.00008)	-3.178 (0.16031)***	-0.009 (0.01297)	0.528
Hub$_t$	0.00022 (0.00010)*	0.116 (0.01688)***	0.010 (0.00287)***	0.894
Hub weigthed$_t$	0.00029 (0.00022)	1.543 (0.12107)***	0.008 (0.01087)	0.578
PageRank$_t$	0.00011 (0.00010)	0.056 (0.01770)***	0.013 (0.00259)***	0.890
PageRank weigthed$_t$	0.00018 (0.00014)	0.074 (0.04348)*	0.009 (0.00490)*	0.801
CheiRank$_t$	0.00017 (0.00009)*	0.098 (0.01577)***	0.009 (0.00227)***	0.885
CheiRank weigthed$_t$	0.00005 (0.00005)	0.287 (0.03349)***	-0.005 (0.00343)	0.781
Random-walk betw.$_t$	0.00012 (0.00007)*	0.009 (0.01260)	0.019 (0.00216)***	0.790
SinkRank$_t$	0.00012 (0.00011)	0.057 (0.01818)***	0.013 (0.00269)***	0.889
SinkRank weigthed$_t$	0.00020 (0.00015)	0.072 (0.04080)*	0.009 (0.00479)*	0.814
SourceRank$_t$	0.00019 (0.00010)**	0.108 (0.01788)***	0.014 (0.00255)***	0.884
SourceRank weigthed$_t$	0.00012 (0.00010)	0.263 (0.03665)***	0.015 (0.00402)***	0.798

Notes: panel-data models with institution fixed effects. Every row presents the results for the model specified for each measure of centrality y_t: y_t = Turnover ratio$_t$ + Transactions share$_t$ + HHI(sovereign debt)$_t$ + ε_t. Estimated parameters are reported on the right-hand side of each column and robust standard errors in parentheses at the left-hand side. Statistical significance at the 1% (***), 5% (**), and 10% (*) levels. The sample period is January 2, 2019, through August 31, 2020. RDA's application to the DCV do not involve an information loss.

Table B.5 First stage of RDA for Deceval

	Turnover ratio$_t$	Transactions share(TDC)$_t$	Transactions share(bonds)$_t$	Transactions share(equities)$_t$	HHI(TDC)$_t$	HHI(bonds)$_t$	HHI(equities)	R^2-Adj
Degree$_t$	0.0063 (0.0023)***	-0.0175 (0.0104)*	-0.0509 (0.0128)***	0.0004 (0.0163)	0.0008 (0.0016)	0.0102 (0.0033)***	0.0005 (0.0023)	0.940
Degree weigthed$_t$	0.0275 (0.0099)***	1.6172 (0.4030)***	-0.3487 (0.0900)***	-0.7376 (0.2034)***	-0.0194 (0.0060)***	0.0181 (0.0092)*	0.0065 (0.0075)	0.635
Indegree$_t$	0.0088 (0.0028)***	-0.0622 (0.0176)***	0.0141 (0.0193)	0.0363 (0.0224)	-0.0017 (0.0022)	0.0095 (0.0044)**	0.0001 (0.0032)	0.915
Indegree weigthed$_t$	0.0311 (0.0089)***	1.9377 (0.4272)***	-0.2867 (0.1059)***	-0.8680 (0.2164)***	-0.0271 (0.0073)***	0.0171 (0.0118)	0.0035 (0.0098)	0.609
Outdegree$_t$	0.0039 (0.0024)*	0.0274 (0.0147)*	-0.1162 (0.0185)***	-0.0357 (0.0220)	0.0032 (0.0020)*	0.0109 (0.0039)***	0.0009 (0.0028)	0.878
Outdegree weigthed$_t$	0.0209 (0.0119)*	0.1236 (0.0563)**	-0.2489 (0.0522)***	-0.0503 (0.0725)	0.0009 (0.0070)	0.0167 (0.0113)	0.0098 (0.0091)	0.474
Closeness$_t$	0.0067 (0.0028)***	-0.3408 (0.1867)*	0.4887 (0.2542)*	0.0832 (0.0737)	-0.0027 (0.0053)	0.0192 (0.0074)***	-0.0135 (0.0071)*	0.101
Closeness weigthed$_t$	0.0050 (0.0022)**	-0.4627 (0.1076)***	0.4187 (0.1215)***	0.1637 (0.0529)***	-0.0040 (0.0039)	0.0103 (0.0051)**	-0.0056 (0.0048)	0.143
Betweennes$_t$	0.0487 (0.0132)***	-0.2082 (0.0693)***	0.0264 (0.0560)	0.1899 (0.0981)*	-0.0043 (0.0097)	0.0333 (0.0177)*	-0.0108 (0.0138)	0.672
Eccentricity$_t$	-0.0005 (0.0013)	0.01 (0.0317)	0.03 (0.0330)	-0.05 (0.0183)***	0.00 (0.0011)	0.0010 (0.0019)	0.0009 (0.0016)	0.134
Eccentricity weigthed$_t$	0.0033 (0.0014)**	-0.1515 (0.0651)***	0.1154 (0.0594)*	0.0654 (0.0364)*	-0.0033 (0.0024)	0.0067 (0.0030)**	-0.0051 (0.0032)	0.102
Eigenvector$_t$	0.0065 (0.0023)***	-0.0227 (0.0149)	-0.0109 (0.0167)	0.0109 (0.0174)	-0.0006 (0.0017)	0.0107 (0.0033)***	0.0011 (0.0025)	0.895
Eigenvector weigthed$_t$	0.0168 (0.0066)***	0.1482 (0.0419)***	-0.0825 (0.0318)***	-0.0443 (0.0390)	-0.0046 (0.038)	0.0125 (0.0064)**	0.0064 (0.0050)	0.732
Authority$_t$	0.0021 (0.0021)	-0.0263 (0.0132)**	-0.0514 (0.0188)***	0.0137 (0.0174)	0.0004 (0.0018)	0.0077 (0.0037)**	-0.0007 (0.0026)	0.911
Authority weigthed$_t$	0.0283 (0.0111)***	2.6657 (0.5857)***	-0.5189 (0.2310)**	-1.2518 (0.3033)***	-0.0148 (0.0144)	-0.0110 (0.0260)	0.0062 (0.0202)	0.212
Hub$_t$	-0.0005 (0.0024)	0.0688 (0.0163)***	-0.1463 (0.0211)***	-0.0705 (0.0181)***	0.0062 (0.0019)***	0.0070 (0.0038)*	0.0035 (0.0027)	0.860
Hub weigthed$_t$	0.0087 (0.0194)	0.0571 (0.0991)	-0.2161 (0.1065)**	0.0446 (0.1498)	0.0067 (0.0165)	-0.0306 (0.0297)	0.0433 (0.0241)*	0.125
PageRank$_t$	0.0081 (0.0024)***	-0.0465 (0.0143)***	0.0024 (0.0166)	0.0340 (0.0212)	-0.0008 (0.0020)	0.0044 (0.0042)	0.0013 (0.0029)	0.884
PageRank weigthed$_t$	0.0245 (0.0059)***	-0.0549 (0.0324)*	-0.0306 (0.0321)	0.0729 (0.0422)*	-0.0009 (0.0041)	0.0088 (0.0077)	-0.0009 (0.0058)	0.646
CheiRank$_t$	0.0055 (0.0022)***	-0.0284 (0.0159)*	-0.0488 (0.0151)***	-0.0046 (0.0218)	0.0015 (0.0019)	0.0080 (0.0037)**	0.0003 (0.0026)	0.819
CheiRank weigthed$_t$	0.0110 (0.0058)*	0.0385 (0.0273)	-0.1276 (0.0252)***	-0.0307 (0.0380)	0.0026 (0.0035)	0.0142 (0.0062)**	0.0013 (0.0047)	0.586
Random-walk bet.$_t$	0.0086 (0.0028)***	-0.1315 (0.0762)*	0.2031 (0.0877)**	0.0324 (0.0388)	-0.0028 (0.0028)	0.0217 (0.0047)***	-0.0067 (0.0047)***	0.466
SinkRank$_t$	0.0085 (0.0025)***	-0.0436 (0.0153)***	0.0004 (0.0179)	0.0426 (0.0230)*	-0.0014 (0.0021)	0.0052 (0.0046)	0.0016 (0.0032)	0.883
SinkRank weigthed$_t$	0.0228 (0.0053)***	-0.0438 (0.0324)	-0.0412 (0.0323)	0.0772 (0.0419)*	-0.0016 (0.0041)	0.0107 (0.0080)	-0.0007 (0.0059)	0.677
SourceRank$_t$	0.0051 (0.0022)**	0.0009 (0.0146)	-0.0663 (0.0156)***	-0.0196 (0.0232)	0.0012 (0.0021)	0.0080 (0.0039)**	0.0004 (0.0028)	0.822
SourceRank weigthed$_t$	0.0087 (0.0053)	0.0871 (0.0388)**	-0.1607 (0.0296)***	-0.0636 (0.0491)	0.0022 (0.0035)	0.0135 (0.0062)**	0.0024 (0.0047)	0.612

Notes: panel-data models with institution fixed effects. Every row presents the results for the model specified for each measure of centrality y_t: y_t = Turnover ratio$_t$ + Transactions share (term deposits certificates)$_t$ + Transactions share (bonds)$_t$ + Transactions share (equities)$_t$ + HHI(term deposits)$_t$ + HHI(bonds)$_t$ + HHI(equities)$_t$ + ε_t. Estimated parameters are reported on the right-hand side of each column and robust standard errors in parentheses at the left-hand side. Statistical significance at the 1% (***), 5% (**), and 10% (*) levels. The sample period is January 2, 2019, through August 31, 2020. RDA's application to Deceval do not involve an information loss.

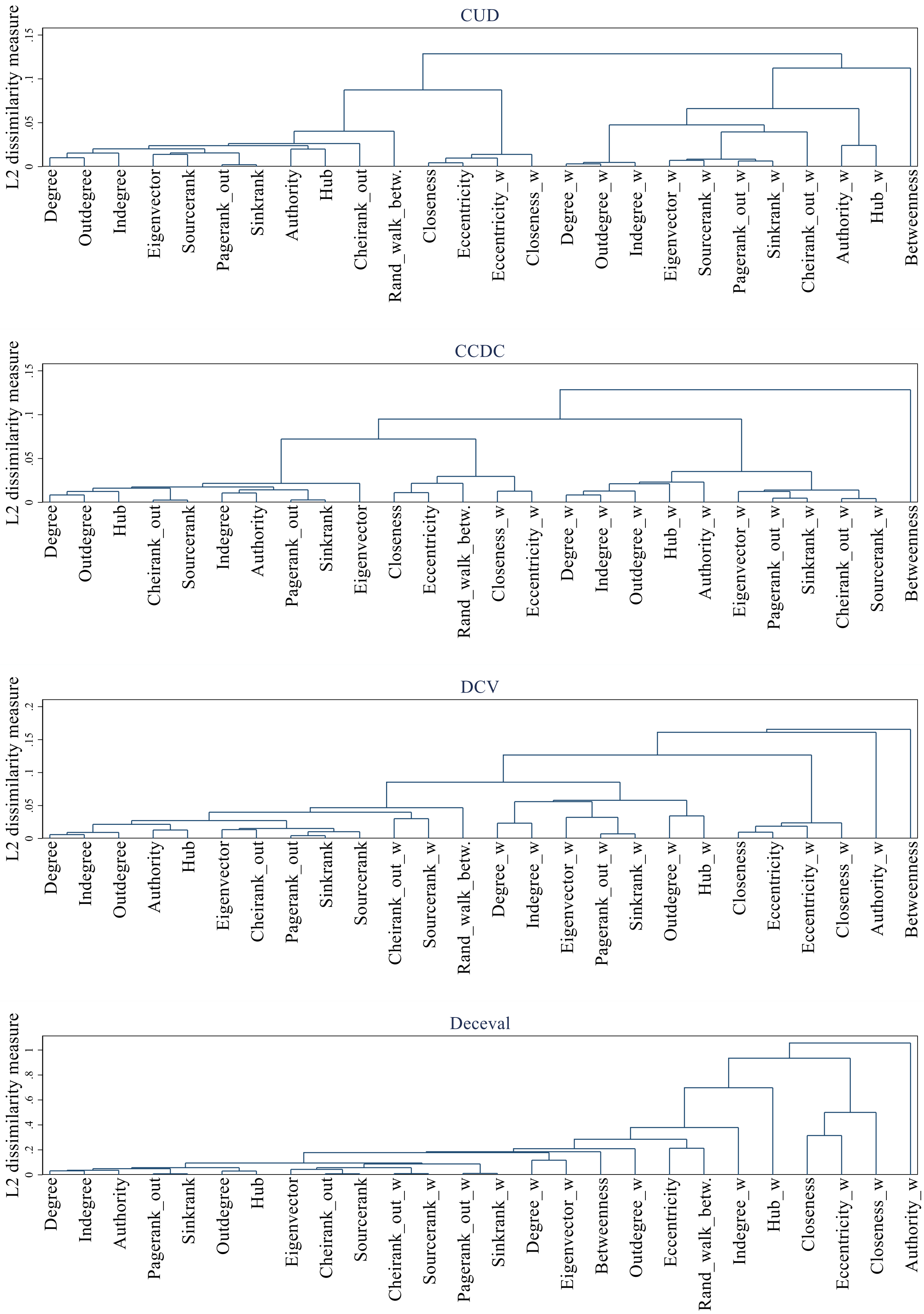
Appendix C. Clustering analysis

Table C.1. Average Euclidean distance to the other centrality measures

Variable	CUD	CCDC	DCV	Deceval
Degree	0.02	0.02	0.02	0.02
Degree weigthed	0.05	0.04	0.04	0.02
Indegree	0.02	0.02	0.02	0.02
Indegree weigthed	0.05	0.05	0.05	0.03
Outdegree	0.02	0.02	0.02	0.02
Outdegree weigthed	0.05	0.04	0.04	0.02
Closeness	0.06	0.05	0.05	0.09
Closeness weigthed	0.06	0.07	0.06	0.16
Betweennes	0.09	0.10	0.10	0.03
Eccentricity	0.06	0.06	0.06	0.02
Eccentricity weigthed	0.06	0.07	0.07	0.06
Eigenvector	0.03	0.03	0.02	0.02
Eigenvector weigthed	0.03	0.03	0.02	0.02
Authority	0.03	0.02	0.02	0.02
Authority weigthed	0.06	0.06	0.10	0.13
Hub	0.03	0.03	0.02	0.02
Hub weigthed	0.06	0.05	0.06	0.07
PageRank	0.02	0.02	0.02	0.02
PageRank weigthed	0.03	0.03	0.03	0.02
CheiRank	0.03	0.02	0.02	0.02
CheiRank weigthed	0.02	0.03	0.02	0.02
Random-walk betw.	0.03	0.04	0.03	0.03
SinkRank	0.02	0.02	0.02	0.02
SinkRank weigthed	0.03	0.03	0.03	0.02
SourceRank	0.02	0.02	0.02	0.02
SourceRank weigthed	0.03	0.03	0.02	0.02
Average distance	**0.04**	**0.04**	**0.04**	**0.04**

Notes: Redundant centrality measures, shaded in gray, exhibit an average Euclidean distance above the average value calculated for each FMI (0.04).

Diagram C.1 Dendrograms using the average-linkage clustering

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