Analysis of the Ecuadorian productive network in 2019, using network theory

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Declaration

Availability of data and materials

The datasets generated and/or analyzed during the current study are available in the Banco Central del Ecuador repository, https://contenido.bce.fin.ec/documentos/PublicacionesNotas/Catalogo/CuentasNacionales/Anuales/Dolares/MenuMatrizInsumoProducto.htm

Competing interests

The authors declare that they have no competing interests.

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Authors' contributions

NM, VC, and CG worked on the introductory and result analysis of the productive network. JR was a major contributor in writing and interpreting the methodology. All authors worked on the calculation and analysis of the centrality indices and the power law.

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Abstract

The present study analyzes the centrality of the 70 productive sectors in Ecuador according to the Input-Output Table for the year 2019, in order to identify the most influential sectors in the diffusion of productivity shocks. For this purpose, four weighted centrality indices are used: Degree Centrality, Closeness Centrality, Betweenness Centrality and Alpha Centrality. The results suggest that the sectors of wholesale and retail trade, transportation and professional activities are the most influential in the Ecuadorian economy, due to their high centrality and participation in the commercial transactions. Furthermore, the distributions of the centrality indices hold the power law which remarks the high heterogeneity of the productive network. Given this, a microeconomic shock to any of these sectors could spread "downstream" cascade effects throughout the intersectoral links and generate aggregate fluctuations, as pointed out by the theory of shock diffusion.

Keywords: Network theory, centrality, heterogeneity, intersectoral links, input-output analysis

1 Introduction

The Ecuadorian productive structure has been characterized by not being very diversified, with a high concentration in the production of primary goods and low incorporation of added value. For example, crude oil represents 31.48%, and traditional products such as bananas, cocoa, coffee, and shrimp, represent 27.91% of total exports, for the year 2019 (Banco Central del Ecuador, 2019). For this same year, the amount of intermediate good transactions in Ecuador was approximately 62 billion dollars, which represented 62.39% of GDP. The sectors that stand out in this exchange are professional, technical and administrative activities, wholesale and retail trade and transport and storage.

According to the methodology of Chenery and Watanabe (1958), which is based on Leontief's input-output model, 8 key sectors can be distinguished in the Ecuadorian economy with high backward and forward linkages, which are: raising livestock; shrimp aquaculture and fishing; extraction of crude oil; manufacture of threads and clothing; production of wood; manufacture of common metals; generation of electrical energy; and financing insurance plans. Among these sectors, the most important key sector in its buyer role (i.e., backward chaining) is Financing insurance plans, since it is necessary to invest 1.37 USD in inputs for each additional dollar in the final demand of this industry. On the other hand, the key sector with the highest forward linkage (i.e., provider role) is Electricity generation, capture and distribution, since this industry increases its production by 1.62 USD for every additional dollar in intermediate consumption.

Although these sectors prove to be of great importance in the Ecuadorian productive network due to their strong forward and backward linkages, there are other sectors that go unnoticed for which an economic shock can generate downstream cascading effects (i.e., from buyer to buyer) and upstream cascading effects (i.e., from supplier to supplier), and produce non-negligible fluctuations in economic aggregates. For example, the sectors with the highest average amount of transactions in the Ecuadorian productive network, and that therefore have a high centrality in the network, technical and administrative activities and wholesale and retail trade, present a 33.26% correlation with GDP growth in the 2019 period. According to Carvalho (2010), and Acemoglu, Carvalho, et al. (2012), this cascade effects are possible thanks to the commercial relations of the productive network since they constitute the main channel to spread and multiply productivity shocks in these highly central sectors and thus generate variations in macroeconomic aggregates. It is in this context where network theory becomes important.

The tools provided by network theory allow a more detailed analysis of the structure of a productive network and complement the analysis of Leontief multipliers on which the identification of key sectors has usually been focused. Here, centrality is one of the most studied aspects to analyze the diffusion of productivity shocks in a productive network. For instance Carvalho et al., ((2013)), Aobdia et al. (2014) and Stella, (2015) study the effects of centrality in the economic growth with econometric tools. It is worth mentioning that this characteristic also includes the resilience of the network, that is, the vulnerability of commercial relationships to random elimination of its sectors. In theoretical terms, centrality allows identifying the most "influential" sectors in an economy, depending on (i) how connected one sector is to another, (ii) the ease of one sector to reach others, (iii) how important a sector is in terms of connecting other sectors and (iv) how central a sector is according to the centrality of its neighboring sectors (Jackson, 2010). To the extent that this centrality is high and is distributed according to a power law, the greater the possibility of spreading productivity shocks in the network (Acemoglu et al., 2012).

In this sense, the use of network theory in the analysis of productive networks can inform both academics about the origins of aggregate fluctuations, and public policy makers about how to prepare for and recover from adverse shocks. Given this, network theory provides the opportunity to analyze the flow of goods and services; the role played by the sectors in the productive system; the detection of market failures and, furthermore, evaluate the effect that the network topology may have on macroeconomic aggregates (Newman, 2010).

In the case of Ecuador, Article 313 of its Constitution stipulates that national production and systemic competitiveness must be encouraged. The latter allows to raise important aspects for business competitiveness from the meta, macro, meso and microeconomic levels; and from a technological, productive, administrative, and operational point of view (Vazquez et. al, 2008). For this, it is necessary to strengthen the commercial relations of the productive network so that they promote sustained sectoral development and lead to a long-term economic growth. Likewise, objective 5 of the National Development Plan (2017) in Ecuador proposes to transform the production matrix, increasing the production of sectors that have a high technological intensity and strengthening links in the production chain.

Under this premise, the main objective of this study is to analyze the structure of the Ecuadorian productive network at the sectoral level, in 2019, through the use of indicators based on network theory. The main hypotheses are: (i) the key sectors identified through the Chenery and Watanabe (1958) methodology, are not necessarily the same sectors of high centrality according to network theory, (ii) the distributions of the centrality measures in the Ecuadorian productive network adjust to a power law.

This study is structured as follows: Section 2 synthesizes the main theoretical and empirical investigations; Section 3 exposes the different tools used; Section 4 shows the preliminary analysis of the Ecuadorian productive network; Section 5 presents the main results; finally, Section 6 presents the main conclusions of the study and the possible recommendations to be implemented in future research.

2 Literature Review

In economics, network theory studies the interrelationships between economic agents in a high interrelated system, in order to describe its structure (Borgatti and Halgin 2011). There exist various applications of network theory in areas like experimental economics, the formation of strategic networks, information and learning diffusion, the labor market, social interrelations and development, negotiation and market power, international commerce and international networks, systemic risk and finance, among others (Jackson 2014b)[1].

In productive networks, the input-output model proposed by Leontief (1951) is possibly the first application of network theory. This model allows to analyze the interdependence of industries in an economic system, considering how the production of one industry is demanded by others as inputs. Based on this work, Hirschman (1958), Rasmussen (1958) and Chenery and Watanabe (1958) establish the analysis of productive chains. Basically, this type of analysis enables to identify the economic sectors that generates large downwards or upwards linkages after an external shock or public policy, taking into account the first and second order effects generated by the commercial interrelationships in the productive network (these effects are estimated from the Leontief multipliers in the conventional input-output model).

From these contributions, the analysis of productive networks has been expanded gradually incorporating different structural characteristics of the economic system with the support of the modern network theory. Here, a prominent field in the analysis of productive networks has been the shock diffusion and aggregate volatility in contrast to the "diversification argument" introduced by Lucas (1977). This argument states that, as the number of economic agents increases, microeconomic shocks tend to “average out” and become negligible by the law of large numbers. That is, in highly disaggregated economies, these shocks do not significantly affect the GDP variation since their magnitude is proportional to $\frac{1}{\sqrt{n}}$, where n represents the number of sectors affected by the shocks.

[1] Generally, the characteristics analyzed in economics through network theory can be divided into two main categories (Jackson 2014a): i) macro-characteristics, such as the density (i.e. high average numbers of connections per node) or the homophily (i.e. the segregation patterns due to the fact that similar nodes tend to be linked to each other), and ii) micro-characteristics, such as centrality (i.e. how nodes are positioned in a network according their connectivity) and transitivity (i.e. the frequency with which two neighbor nodes of a given node are connected).

The work of Acemoglu et al. (2012) is one of the main references on diffusion in productive networks that rejects Lucas' argument. Based on a general equilibrium model with perfect competition, these authors argue that a microeconomic shock can spread in the economic system and generate macroeconomic fluctuations, through the linkages of the productive network. On the one hand, the commercial relationships propagate shocks from one sector to its neighbors (i.e. first-order interconnections) and extend these effects to other interrelated sectors (i.e. higher-order interconnections) in the productive network. The authors measure this aspect using the alpha centrality which is based on Leontief multipliers. On the other hand, if the role of sectors as input suppliers is highly heterogeneous such that the power law holds, idiosyncratic shocks have a large effect on macroeconomic fluctuations. According to the authors, both characteristics allow to diffuse shocks from buyer to buyer on the network, generating the so called "downstream" cascade effects.

Carvalho (2014) shows the importance of Acemoglu's results in the analysis of aggregate volatility, using data from the United States' production network. According to Carvalho, this network as others can be characterized as a small world (i.e., low diameter, low average distance), where economic sectors are found in a few input-output relationships from each other. This network is also characterized by a high heterogeneity in input provision (i.e. the power law holds in the degrees' distribution) and highly central economic sectors. These properties explain the dynamics of two interesting phenomena. First, the proximity between different economic sectors is highly correlated with the co-movements of their economic activity. The closer they are, the higher is the probability that their activity occurs simultaneously. Second, the activity of the most central sectors in the US' production network is highly correlated with GDP growth. The latter suggests that sectors that are more central are an important source of aggregate fluctuations since they enable the synchronization of the remaining sectors' activity in the productive network.

All of these evidences follow Jackson (2014a)'s claims about propagation from one economic agent to others based on the macro and micro-characteristics of a network. On the one hand, macro-characteristics such density and homophily, can explain the propagation from one economic agent to others meanwhile segregation could slow diffusion. On the other hand, micro-characteristics, such as centrality and transitivity can explain how the behavior of economic agents is interrelated in this process. Highly central agents have economic and social power, and can influence rapidly the decisions of other agents. Likewise, high interconnectivity in a network on a local level (i.e. transitivity) is important in encouraging "cooperative" behaviors regarding bargaining.

Several investigations about diffusion in productive networks share the theoretical approach proposed by Acemoglu et al. (2012) in competitive markets, remarking the importance of sectors' centrality and its power law distribution for the generation of "downstream" cascade effects (V. Carvalho and Gabaix 2013; Jones 2013; V. M. Carvalho 2014; Stella 2015; Bigio and La'O 2016; Gabaix 2016; Atalay 2017; Acemoglu, Ozdaglar, and Tahbaz-Salehi 2017). Other studies that consider high substitution between inputs and labor (V. M. Carvalho et al. 2016), shocks on the demand side (Acemoglu et al. 2016), industrial organization (Grassi 2017) or entry-exit firms (Baqaee 2018), also state the importance of sectors' centrality in the productive networks for the generation of "upstream" cascade effects, instead. That is, shocks propagate from supplier to supplier.

3 Methodology

The main feature to describe in this study, as mentioned in the theory for shock diffusion, is the sector's centrality. To this purpose, the Ecuador Input-Output Matrix for the year 2019 is used. This matrix shows the intersectoral commercial relationships between 70 productive sectors, divided according to the International Standard Industrial Classification (ISIC). This information was obtained from the System of National Accounts elaborated by the Central Bank of Ecuador. The identification number of the sectors in this matrix, as well their classification according to the Chenery and Watanabe methodology (CW classification), is shown in the appendix A.

In order to explain the methodology, the Ecuadorian productive network will be represented as a directed and weighted graph $G = (N, A)$, where $N = \{1, \dots, n\}$ is the set of productive sectors (i.e. vertices) and $A = \{a_{ij}\}_{n \times n}$ is the adjacency matrix of the productive network (i.e. edges). Here, $a_{ij} \in \{0,1\}$ represents the commercial relationship between the sector i and the sector j. If $a_{ij} = 1$, then the sector i sells to the sector j; otherwise, if $a_{ij} = 0$, the sector i does not sell to the sector j. Let $w: A \rightarrow \mathbb{R}_+$ be the weighting function that assigns to each intersectoral link a_{ij} the amount $w_{ij} = w(a_{ij})$ that the sector i sells to the sector j.

The weighted centrality indices that will be applied on the Ecuadorian productive network are explained below. Fuentes & Sastré Gutiérrez (2001), Newman (2001), Brandes (2001), Barrat et al. (2004) and Opsahl et al. (2010) are main references for these indices.

3.1 Weighted Degree centrality

The weighted degree centrality $C_i^d(G)$ measures the total amount of direct commercial relationships that a vertex i makes with others. This index is calculated as follows:

$$C_i^d(G) = \sum_{j}^{n} w_{ij}, \quad \forall\, i = 1, \dots, n \tag{1}$$

where n is the total number of vertices in the network. If this centrality index has a high value, the amount of direct commercial relationships for an economic sector is high, and therefore it is more central in the productive network.

3.2 Weighted Closeness centrality

The weighted closeness centrality $C_i^c\,(G)$ measures the inverse of farness, which in turn, is the sum of distances of vertex i to all other nodes (Newman, 2001). Here, the distance is determined by applying the Dijkstra's algorithm (1959)[2] onthe inverse of commercial relationships. This index is calculated as follows:

$$C_i^c\,(G) = \frac{1}{\sum_j^n d_{ij}^{\alpha}}, \qquad \forall\, i = 1, \dots, n \tag{2}$$

where d_{ij}^{α} is the length of the shortest path between vertex i and vertex j, based on the inverse of the commercial relationships. This length is measured as:

$$d_{ij}^{\alpha} = \min_{\phi \in \Phi_{ij}} \sum_{(r,s) \in \phi} \frac{1}{(w_{rs})^{\alpha}}$$

where Φ_{ij} are all possible paths between vertex i and vertex j, (r, s) is an edge that belongs to the path ϕ and α is a synchronization parameter. This parameter is equal to 1 to exclusively consider the amounts of the commercial relationships in network for the calculation of the index.

[2] Dijkstra (1959) proposes an algorithm that determines the shortest path for a pair of vertexes in a graph, taking into account the weights of each edge as costs.

A high closeness centrality indicates than an economic sector maintains a close relationship with the rest of the sectors in the productive network, due to the high commercial amounts. Its reciprocal value could give an idea of the average number of commercial transactions between one sector with their final buyers.

3.3 Weighted Betweenness centrality

The weighted betweenness centrality $C_i^b\,(G)$ shows how well a vertex i is located, according to the geodesic paths between all vertices in the productive network, using the Dijkstra's algorithm (1959). This index is calculated as follows:

$$C_i^b\,(G) = \sum_{i|i\notin\{j,k\}} \sum_{j|j\notin\{i,k\}} \frac{p_{ij}^{\alpha}(k)}{p_{ij}^{\alpha}}, \qquad \forall\, i = 1,\dots,n \tag{3}$$

where p_{ij}^{α} is the number of geodesic paths between vertices i and j, and $p_{ij}^{\alpha}(k)$ is the number of geodesic paths between vertices i and j passing exclusively through vertex k $\left(p_{ij}^{\alpha}(k) < p_{ij}^{\alpha}\right)$. In order to identify these geodesic paths, the distance is measured as:

$$d_{ij}^{\alpha}(k) = \min_{\phi\in\Phi_{ij}(k)} \sum_{(r,s)\in\phi} (w_{rs})^{\alpha}$$

where $\Phi_{ij}(k)$ are all possible paths between vertex i and vertex j with an intermediate vertex $k \notin \{i,j\}$, (r,s) is an edge that belongs to the path ϕ and α is the synchronization parameter. This parameter is equal to 1 when considering the amounts of the commercial relationships in network.

When the weighted centrality index of betweenness takes high values, an economic sector appears more frequently in the geodesic paths that connects all pairs of sectors in the productive network.

3.4 Weighted Alpha Centrality

The weighted alpha centrality $C^{a}(G)$ determines the influence of vertex i towards its neighbors and the neighbors of its neighbors, through exogenous shocks in the network. This influence is measured by adding the amounts of purchases and sales that vertices i carries out with other sectors. Therefore, the alpha index is proportional to the sum of the amounts of the vertices to which it is connected. This index is calculated vectorially as follows:

$$C^{a}(G) = (I - \omega W^{T})^{-1} e \tag{4}$$

Where W^T is the transpose of the weighted adjacency matrix $W = \{w_{ij}\}_{n\times n}$, ω is a parameter that reflects the relative importance of endogenous factors in determining the centrality, e is a vector of exogenous perturbations[3] and I is the identity matrix.

If the value of the alpha index is high, then the sector is central because its neighboring sectors have high commercial exchange. This index is analogous to the dispersion sensitivity index proposed by Rasmussen (1958), which measures how important a sector is in the forward linkage of a productive network (Fuentes and Sastré Gutiérrez 2001).

4 Preliminary analysis of the Ecuadorian productive network

In the Ecuadorian productive network, there are few big sectors that are suppliers and buyers of the majority of other sectors. This generates a star/like pattern of intersectoral relations, as shown in **Figure 1**. The industries with the highest level of commercial exchange are construction (number 53 in figure), wholesale and retail (54), transport (58) and professional services (64).

This is consistent with the center-periphery model of Everett and Borgatti (1999), where a group of sectors with strong links are found in the center of the network, while weakly connected sectors are relegated to peripheral positions (González and Fernández, 2008). Given this structure, there is a possibility that a microeconomic shock in these sectors could spread across the network and generate macroeconomic fluctuations, as proposed by Acemoglu et al. (2012). This author mentions that idiosyncratic shocks to central nodes in a "star network" are not averaged (i.e., their effect spreads across the productive system), due to the presence of first and second order interconnections that magnify the effect over the entire network.

[3] In the present study, the exogenous factor e is a vector of 1, because only the structure of the productive network is analyzed.

Figure 1. Graph of the Ecuadorian productive network

Source: Input-Output Matrix-Central Bank of Ecuador (2019).

Note: This graph shows the Ecuadorian cross-sectoral network according to the input-output matrix 2019. Vertices represent the 70 productive sectors of the economy, and their size shows their added value. The identification number of these sectors is shown in the appendix A. This figure is obtained by the Fruchterman-Reingold algorithm that accounts the weight of the vertices; vertices inside (outside) the network has a higher (lower) commercial exchange. On the other hand, edges represent the amount of buying and selling transactions; and its size indicates the amount of the transaction made between two sectors. For graphic purposes, only transactions larger than $77 million are considered.

In **Table 1**, the main characteristics of the Ecuadorian productive network are shown. The number of edges show that most of the 70 sectors (number of vertices) are related to each other through 4,510 buying and selling transactions. If all sectors were related to each other, 4,830 (70*69) edges would be possible. In the Ecuadorian case, 93% (network density) of the possible transactions take place. This high density indicates that most sectors are directly related to each other (Coleman and Moré 1983). The diameter indicates that a maximum of 2 transactions are required to be able to reach from one sector to another, considering the shortest linkages in the network. The length of the average path between sectors is 1.04 transactions; that is, for one sector to be related to another it must perform at least 1 transaction approximately. The total non-weighted degree indicates that a sector records an average of 129 buy-and-sell transactions. The average amount of these transactions is USD$ 1,581.36 million (total weighted degree). In addition, one sector maintains business relationships with approximately 65 buyers (in-degree) and 65 suppliers (out-degree). The sectors of extraction of crude oil (12), manufacturing industries (50), transport and storage (58) and private teaching services (66) are buyers with the highest number of connections (66 in-degree), while postal and mail activities (59) have the lowest quantity of relationships, corresponding to 54. On the other hand, suppliers maintain a maximum of 70 (non-weighted out-degree) direct transactions on the network, however, manufacturing of tobacco products (32), public education services (non-market) (67) and health and social services (non-market) (69) have 0 out-degree connections.

Table 1. General statistics of the Ecuadorian productive network

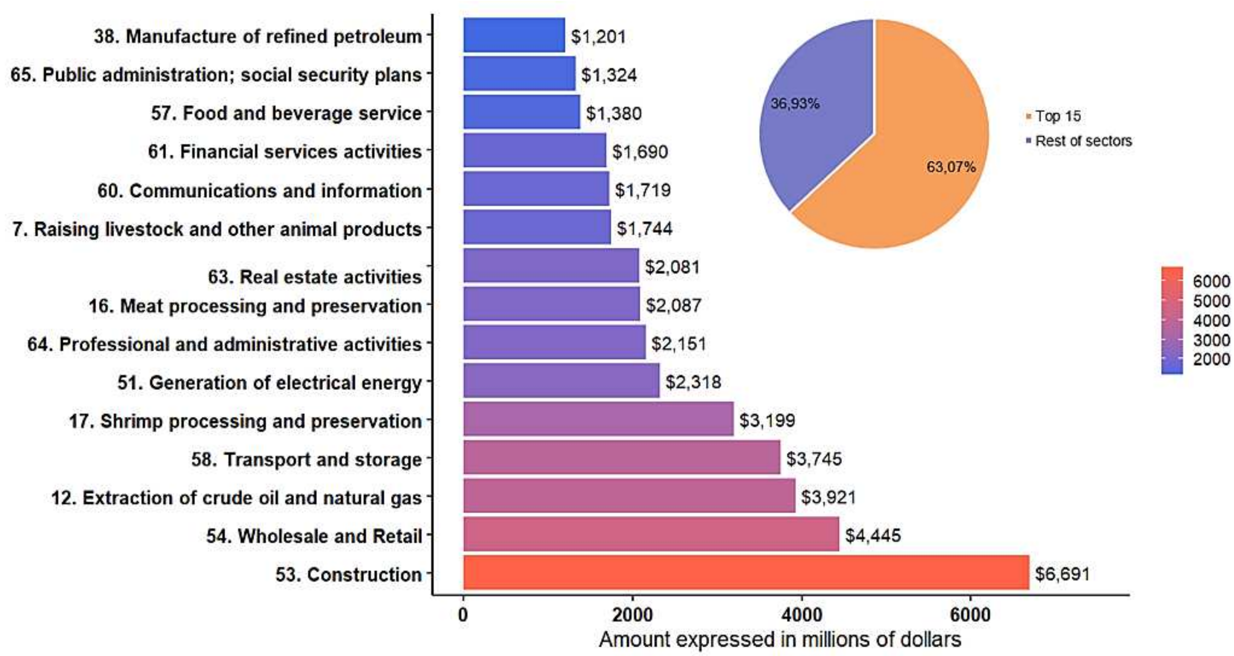
Characteristics	Statistics
Number of vertices	70
Number of edges	4,510
Density	0.93
Diameter	2.00
Average path length	1.04
Total non-weighted degree	128.86
Total weighted degree (millions of dollars)	1,581.36
Non-weighted in-degree	
Mean	64.43
Minimum	54
Maximum	66
Non-weighted out-degree (mean)	
Mean	64.43
Minimum	0
Maximum	70

Source: Input-Output Matrix-Central Bank of Ecuador (2019).

Note: The number of vertices indicates the productive sectors. The number of edges represents the amount of sale transactions between the sectors. Density is the relative fraction of transactions present on the network. The diameter of a network is the largest geodesic path between two sectors. The length of the middle path is the average distance between two sectors. The average total grade without weights (with weights) is the number (amount) of average purchase (with a minimum of 54 transactions and a maximum of 66) and sale transactions of the sectors (with a minimum of 0 transactions and a maximum of 70).

Considering the total demand and supply, the Ecuadorian productive network records an amount of USD$ 62,935 million. The total demand from the economic sectors is shown in **Figure 2**. It is evident that the demand is concentrated in few sectors and that the gap between the first demanding sector and the next sectors is quite large. The construction sector records the highest demand for inputs, with USD$ 6,691 million, representing 10.63% of the total intermediate consumption at basic prices. The next sectors with the highest input demand are the wholesale and retail trade (54) and oil and natural gas extraction (12), with USD$ 4,081 million (6.80%) and USD$ 3,650 million (6.08%), respectively. The rest of the sectors (67 sectors) demand USD$ 23,239 million, despite that most of the sectors are interconnected (high density of 93%), few of them are highly interconnected because of their demand.

Figure 2. Demand by economic sectors, 2019

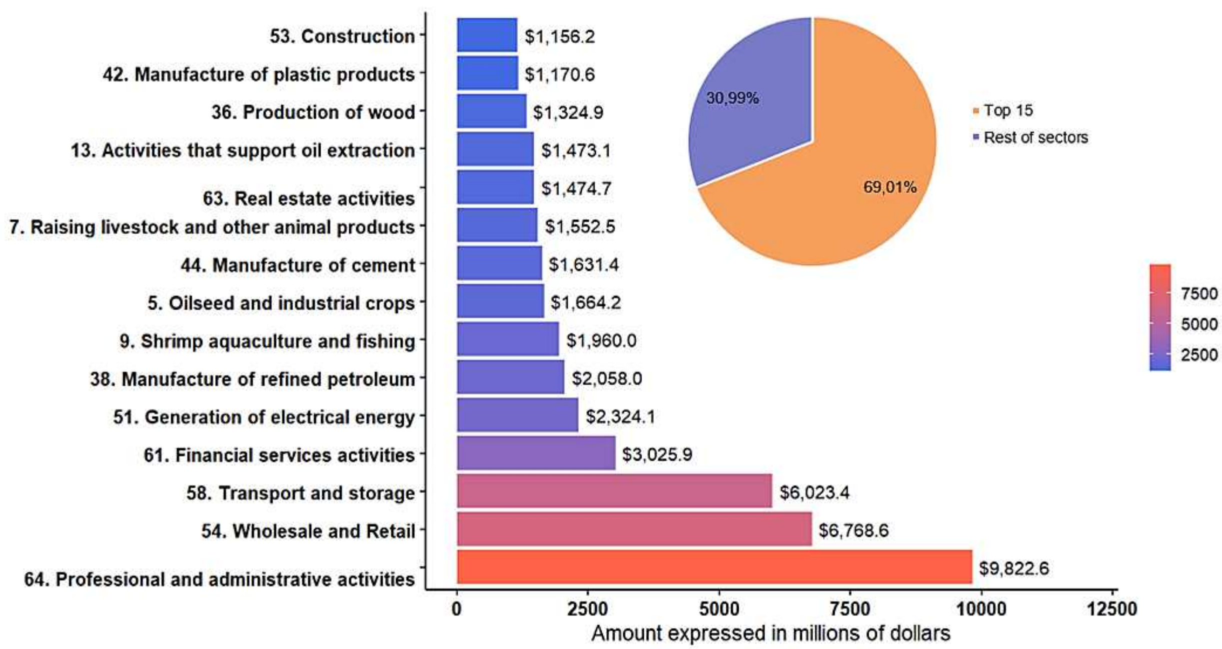


Source: Input-Output Matrix-Central Bank of Ecuador (2019).

Note: The bar chart represents the total intermediate consumption by sector of the Ecuadorian economy. The horizontal axis indicates the demand for each sector in millions of dollars, while the vertical axis indicates the 15 sectors with the highest demand in the country. In addition, the color of the bars shows the intensity of consumption in the sectors. The more tomato (blue) this color is, the higher (lower) its consumption.

The supply of economic sectors is shown in **Figure 3**. The distribution of the supply is highly concentrated in few sectors but to a lesser extent than the demand. The first three supply sectors record shares around 10% each one. The sector with the highest supply corresponds to professional, technical, and administrative activities (64), which sells USD$ 9,823 million (15.61% of total production). It is very interesting that this sector is the main supplier to other sectors because it means that other sectors are performing based on training and technical assistance In particular, this sector mainly provides services to itself (9.67%), to the wholesale and retail sector (54) with 8.64%, to the communications and information sector (60) with 8.17% and to transport and storage (58) with 8.04% of its total production. The second and third most important supply sectors are wholesale and retail, and transportation, which supply a total of USD$ 6,769 million and $USD 6,023 million (10.75% and 9.57%, respectively).

Figure 3 Supply by economic sectors, 2019



Source: Input-Output Matrix-Central Bank of Ecuador (2019).

Note: The bar chart represents the total production by sector of the Ecuadorian economy. The horizontal axis indicates the production of each sector in thousands of dollars, while the vertical axis indicates the 15 sectors with the highest production in the country. In addition, the color of the bars shows the intensity of the production of the sectors. The more tomato (blue) this color is, the higher (lower) its production.

5 Results

5.1 The centrality in the productive network

Some authors such as Jackson (2010), Newman (2010), Acemoglu, Carvalho, et al. (2012), Aobdia, Caskey, and Ozel (2014), Carvalho (2014) and Carvalho et al. (2016), highlight the relevance of identifying the sectors with the greatest centrality in the economy, since an idiosyncratic shock to these can cause cascade effects and therefore macroeconomic fluctuations. Hence, centrality measures provide important information on the capacity of industries to spread and expand shocks on the productive network.

5.1.1. Centrality Analysis

Table 2 shows the descriptive statistics of the results regarding the weighted centrality indices of degree, closeness, betweenness[4] and alpha centrality for the 70 industries in the Ecuadorian network, using the Input-Output Matrix 2019. In order to visualize the centrality of the industries in the productive network, each of the centrality indices are plotted in the panels of **Figure 4**, using a color scale for the nodes: if the node is redder (blue), its centrality index is higher (low).

Table 2. Centrality measures statistics

Weighted Centrality measure	Mean	Std. Dev.	Min	Max
Degree	$1,798.14	2410.25	$33.12	$11,973.75
Closeness	0.03287	0.01935	0	0.07855
Betweenness	187.7	517.5742	0	2910
Alpha	1.604	1.07373	1	7.815

Source: Input-Output Matrix-Central Bank of Ecuador (2019).

Note: The table shows two statistical moments (i.e. mean and variance) that characterize the distributions of the weighted centrality indices.

[4] The synchronization parameter α used in the closeness and intermediation centrality index was set to 1 to consider only the amounts of transactions between sectors.

Figure 4. Graphs of Weighted Centrality Indices

Panel A) Degree Centrality

Panel B) Closeness Centrality

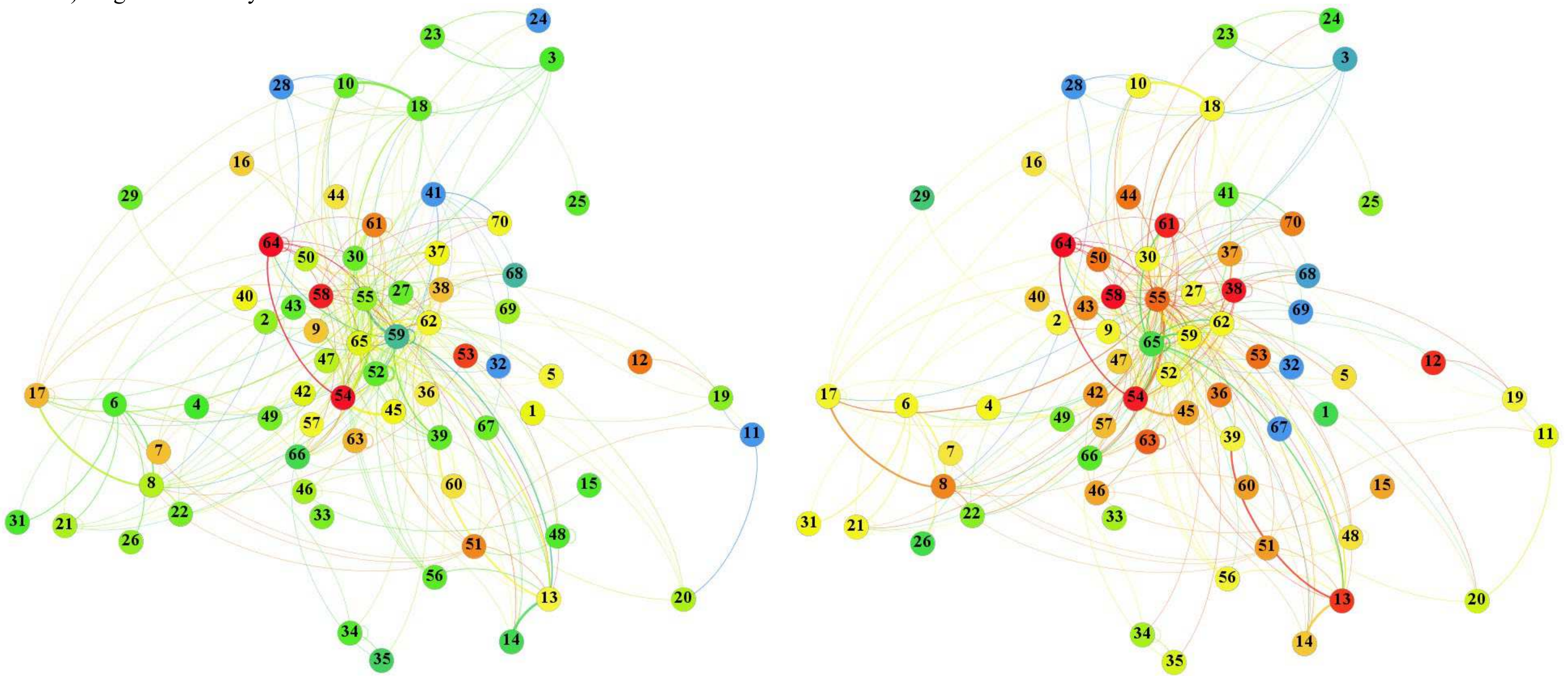
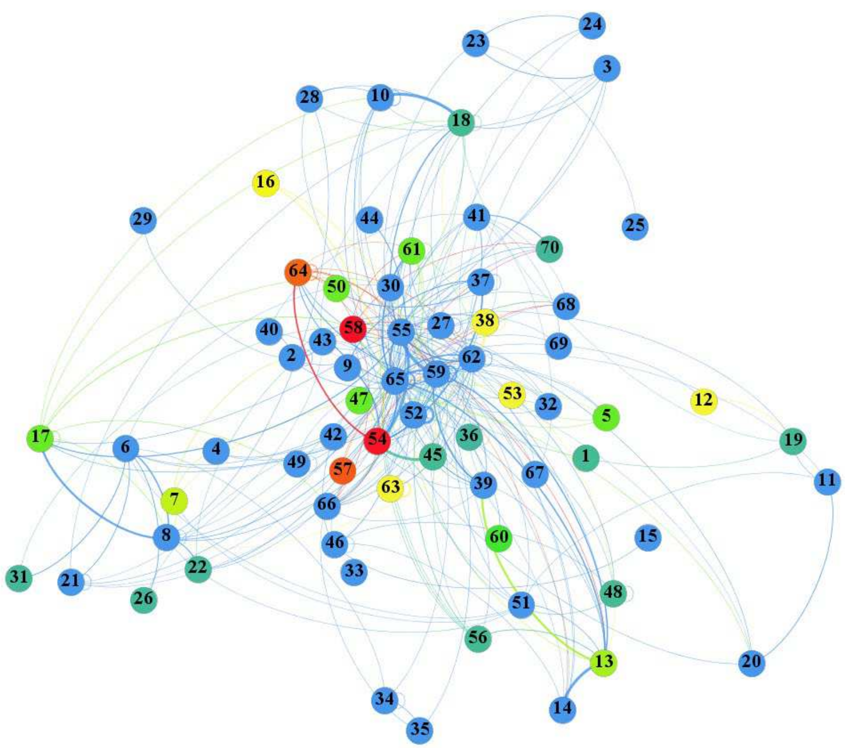
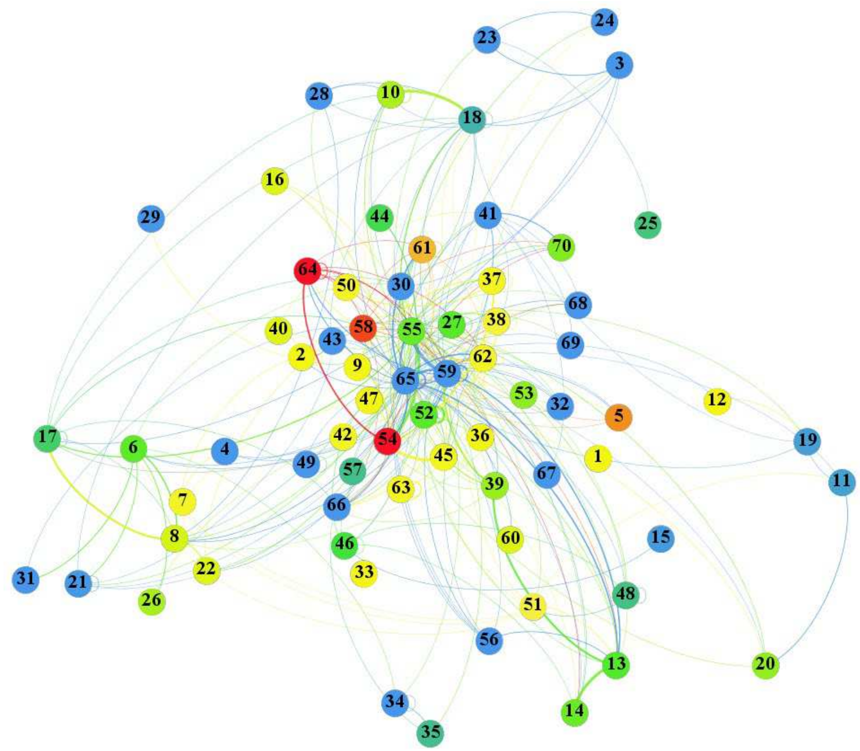


Figura 4 (continuation). Graphs of Weighted Centrality Indices

Panel C) Betweenness Centrality



Panel D) Alpha Centrality



Note: The Figure shows the indexes centrality of degree, closeness, betweenness and alpha in the Ecuadorian productive network. The vertices represent the 70 productive sectors. The identification number of these sectors is shown in the appendix A. The color of the vertices is related to the weighted centrality indices; that is, if the node is redder (blue), its centrality index is higher (lower). In addition, the edges indicate the sale transactions greater than 31 million dollars, which occur between the sectors, if it is wider (thin), it shows that the amount of the transaction is higher (lower).

According to the degree-weighted centrality index (**Figure 4** - Panel A), commercial relationships of the productive sectors in Ecuador show high variability. The mean of the degree-weighted centrality is USD$ 1,798.14 million. There are 20 sectors that are above the mean and 50 sectors below the mean. There are 4 sectors that trade amounts greater than 7 billion dollars. The sectors that most boost the economy, by recording high level first-order relationships with suppliers and buyers, are professional activities (64), wholesale and retail (54), transportation (58) and construction (53). On the other hand, the sectors that record a low level of first-order relationships are: manufacture of tobacco products (32), manufacture of rubber products (41) and manufacture of farinaceous products (24).

The closeness index (**Figure 4** - Panel B) shows a great number of sectors that have a high proximity. These sectors are suppliers that rapidly interact with various industries in the network. This aspect facilitates a quick access to inputs by suppliers and to carry out their production process. The mean of this index is 0.0329 and there are 31 sectors above the mean and 39 below it. The sectors that are closer to others are: professional activities (64), transportation (58), manufacture of refined petroleum products (38) and wholesale and retail (54). These sectors are close to others because they are direct providers in the productive network. This relationship promotes commercial interaction, without the need for many intermediaries, which makes the exchange more dynamic in the productive network. The sectors that are far away from suppliers and that need many intermediaries to carry out their production process are: manufacture of tobacco products (32), public (non-market) education services (67) and non-market health and social services (69).

The betweenness centrality index (**Figure 4** - Panel C) shows a polarized network, with only four sectors (circles 54, 58, 57 and 64) that actively participate intermediating between sectors and the rest of the sectors (66 sectors) participate to a lower extent intermediating transaction like manufacture of tobacco products (32), public (non-market) education services (67) and non-market health and social services (69). The mean of the betweenness-weighted centrality is 188 transactions, and there are 10 sectors that are above the mean and 60 sectors below it. The high intermediary sectors are transportation (58), wholesale and retail (54), food service (57) and professional activities (64). These sectors are in strategic positions in the network since they channel transactions more efficiently in the economy. By contrast, the rest of sectors depend on those strategic sectors, so that a shock in the strategic sectors would affect them.

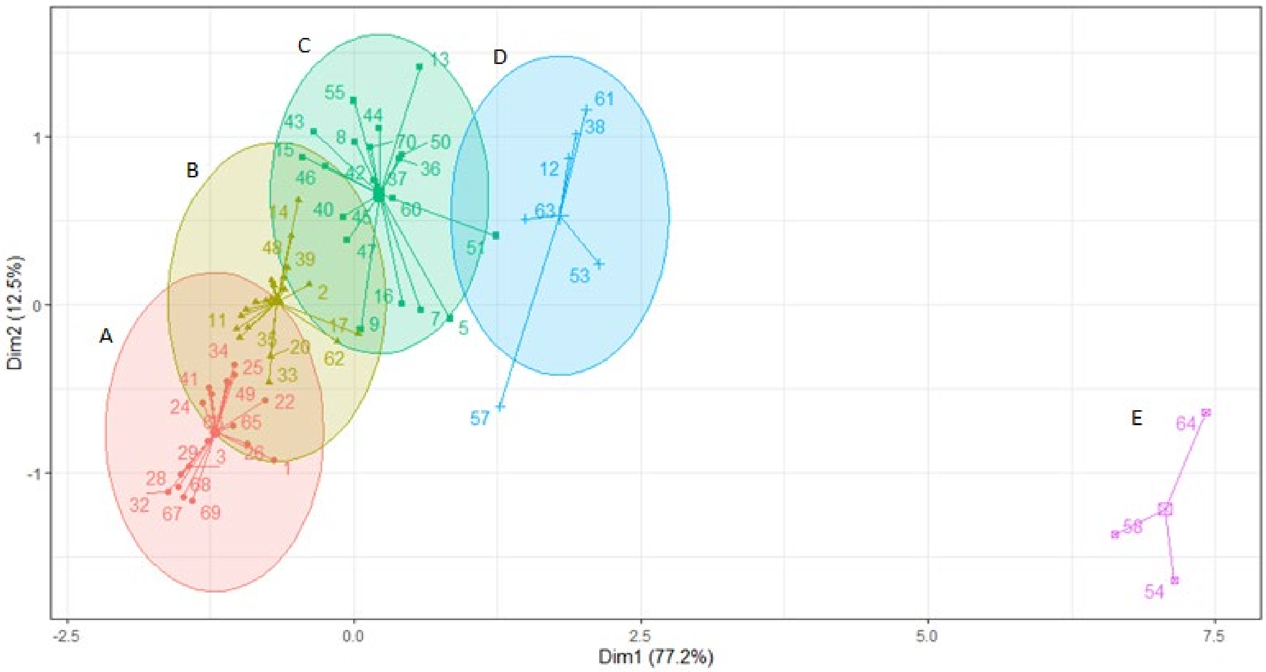
The alpha centrality index (**Figure 4** - Panel D) shows few sectors of high importance in commercial exchange, considering the relationship with other industries that also trade high amounts. However, it presents a more balanced image than that shown in the betweenness index. The mean of the alpha-weighted centrality is 1.60, and there are 18 sectors that are above the mean and 52 sectors below it. Among the most central sectors, there are professional activities (64), wholesale and retail (54), transportation (58) and oilseed and industrial crops (5), where a negative shock will probably affect the client-industries of these sectors. In Contrast, the sectors recording the lowest alpha centrality are manufacture of tobacco products (32), public (non-market) education services (67) and non-market health and social services (69). This means that they are slightly connected downward in the productive network.

For more information, the appendix B shows the top 7 industries (that is, 10% of economic sectors) with the greatest centrality in each of the four indices.

5.1.2. Clustering according to the centrality indices

Based on the four centrality indices, a clustering analysis is conducted to determine similarities in terms of centrality between sectors. In Figure 5, Dimension 1 is explained by the degree, betweenness and alpha centrality indices in a 77.2%, while dimension 2 is explained by the closeness centrality index in a 12.5%.

Figure 5. Clustering K-means according to centrality indices.



Source: Input-Output Matrix-Central Bank of Ecuador (2019).

Note: The variables that explain most of dimension 1 are the indexes of degree centrality, betweenness and alpha, meanwhile the index of closeness explains dimension 2. The identification number of the sectors is shown in the appendix A.

Cluster A records the lowest mean value of all four indices, simultaneously cluster E records the highest mean value in the four indices. The average centrality of each of these indices is increasing across clusters (as seen in **Table 3**), starting with cluster A, and then heading to cluster E. The setting of these clusters according to the centrality indices can be seen in Appendix C. A special emphasis is given to the sectors with high centrality measures in the Clusters D and E, because of their high capacity to diffuse productivity shocks, to generate cascade effects and to generate macroeconomic fluctuations, as argued by Acemoglu, Carvalho, et al. (2012). Among them, according to the CW classification, there are six base sectors, one motor sector, one island sector and one key sector. In other words, it can be argued that the CW classification loses sight of sectors that are relevant in terms of their transactionality, proximity, betweenness and linkages. With the CW classification, only one sector (Extraction of crude oil and natural gas) is identified as key sector that promotes production, by demanding and offering large amounts of inputs to the rest of the sectors.

Table 3. Mean and standard deviation of the five clusters.

Weighted Centrality measure	A	B	C	D	E
Degree	-0.50493419	-0.42779478	0.0326936	1.06311998	3.81167168
	(0.1708326)	(0.2939015)	(0.4264474)	(0.850301)	(0.464744)
Closeness	-1.21659698	-0.27735214	0.65752358	1.32077974	2.08927301
	(0.335377)	(0.2625178)	(0.3946588)	(0.529669)	(0.271558)
Betweenness	-0.33729694	-0.32137184	-0.2316300	0.99745536	4.00700784
	(0.04998127)	(0.0734186)	(0.16652811)	(0.869868)	(1.568726)
Alpha	-0.44877617	-0.30826972	0.05248136	0.26091072	4.06411069
	(0.183409)	0.2244653)	(0.4689618)	(0.616187)	(1.63401)

Source: Input-Output Matrix-Central Bank of Ecuador (2019).

Note: These are the means and standard deviations of the centrality indices for each of the clusters.

The three sectors of cluster E represent the 22.71% of the GDP and these are: wholesale and retail (54), professional activities (64) and transportation (58). These three sectors correspond, according to the CW classification, to base sectors; that is, they mostly generate forward linkages.

The professional, technical, and administrative activities (64), as shown in the metrics of **Table 4**, commercialize the highest amount of purchase and sale transactions, corresponding to USD$ 11,973.8 million and participate in 1,351 transactions out of a total of 4,510 (29.96%). This sector can reach its final buyers with around 12 commercial transactions (1/closeness = 1/0.0785). In addition, the professional, technical, and administrative activities increase their production by USD$ 7.81 for each additional dollar in intermediate consumption in this sector.

Wholesale and retail trade (54) is part of 2,524 transactions (55.96%) and trades directly with other sectors around USD$ 11,213.3 million, providing a great amount of inputs to the rest of the sectors. In addition, for each additional dollar in intermediate consumption in wholesale and retail, the production of this sector increases by USD$ 5.76 towards other activities. It takes approximately 14 (1/closeness = 1/0.068) commercial transactions in the productive network to attain its final buyers

The transportation and storage sector (58) trades around USD$ 9,768.6 million dollars and it is part of 2,910 transactions (64.52%) in the production network. This sector is in charge of accelerating the Ecuadorian economy, because it promotes economic growth and development (Fernández, 2017). This sector can reach its final buyers with around 13 (1/closeness = 1 / 0.0733) commercial transactions. For each additional dollar in intermediate consumption of transportation and storage, its production increases by USD$ 4.32 towards other activities.

Cluster D is made up of 7 sectors that represent 27.83% of GDP. These sectors are mainly services, real estate activities and issues related to oil activities. The construction sector (53) stands out in the degree centrality, while financial services activities (61) with manufacture of refined petroleum (38) stand out in closeness centrality. On the other hand, food, and beverage services (57) predominate in the betweenness centrality, while financial services activities (61) stand out in the alpha centrality.

Table 4. Main sectors according to the centrality indexes.

Cluster	Id	Sector	Degree centrality	Closeness centrality	Betweenness Centrality	Alpha Centrality	CW categorization
Cluster E	64	Professional and administrative activities	11,973.8	0.0785	1351	7.8151	Base
	54	Wholesale and retail	11,213.3	0.0680	2524	5.7642	Base
	58	Transport and storage	9,768.6	0.0733	2910	4.3239	Base
Cluster D	53	Construction	7,847.6	0.0529	629	1.3771	Isle
	12	Extraction of crude oil and natural gas	4,970.7	0.0645	642	1.6016	Key
	61	Financial services activities	4,715.9	0.0669	132	2.9428	Base
	57	Food and beverage service	1,814.8	0.0417	1523	1.1667	Motor
	63	Real estate activities	3,555.4	0.0559	653	1.8680	Base
	38	Manufacture of refined petroleum and other products	3,258.7	0.0685	645	2.3488	Base

Source: Input-Output Matrix-Central Bank of Ecuador (2019).

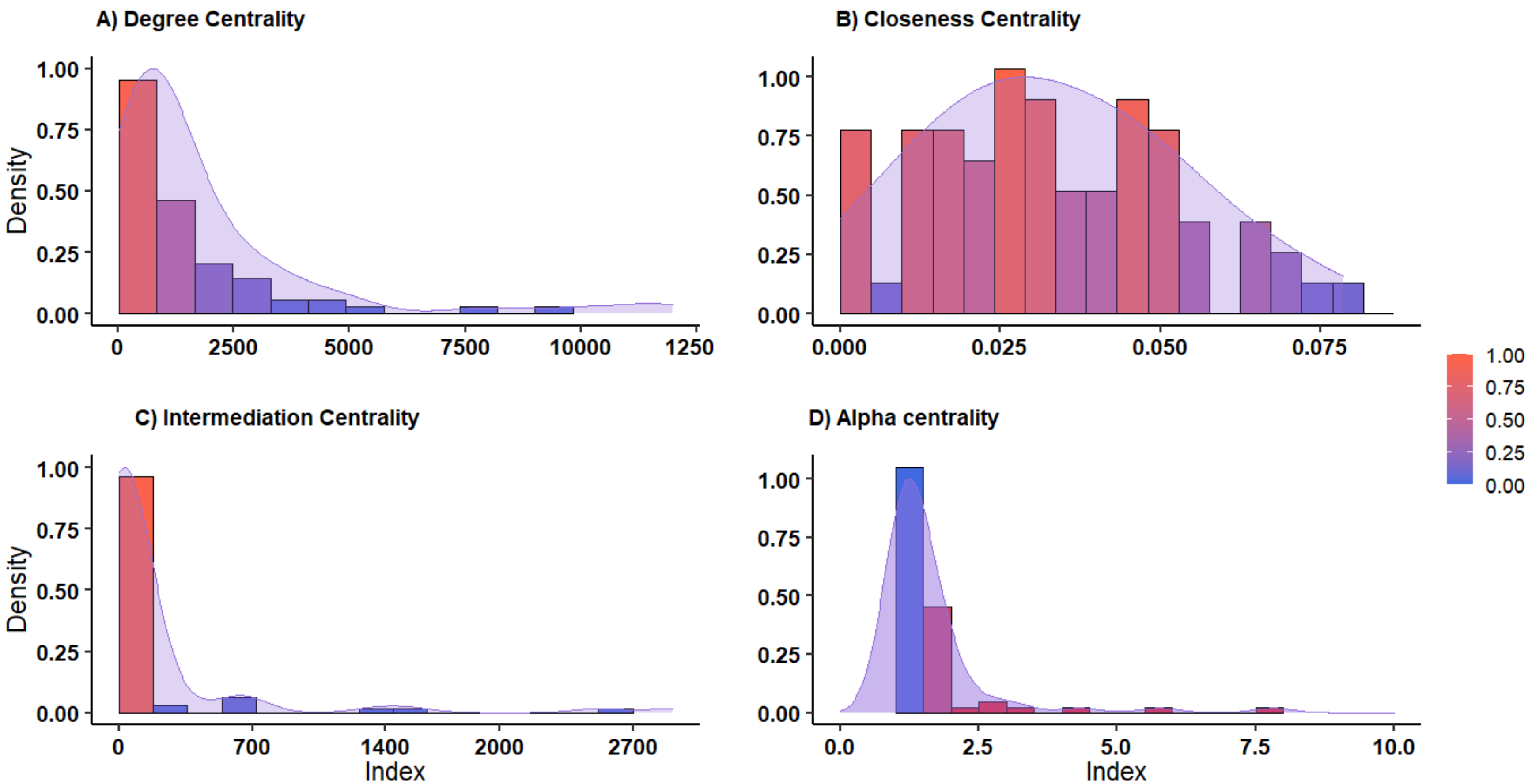
Clusters A, B and C are mostly made up of primary activities, intensive in labor, belonging to informal sectors like agriculture, farming of cattle, fishing, and forestry. Given that Ecuador is a primary-exporter economy, it is striking that these sectors are among these clusters and not in clusters D and E with greater centrality. These primary sectors consolidate the productive matrix by generating high foreign exchange earnings and, therefore, a high share of GDP. This phenomenon is due to the fact that exports continue to be commodities with low added value, which is why they generate low local transactionality. Therefore, the fact that these sectors are not highly central could be considered as a good thing, since a shock to these sectors would not affect the rest of the productive network.

5.2. Power Law

Productive networks are characterized by high heterogeneity of the sectors' centrality in commercial transactions. This phenomenon is regularly characterized through a power law distribution (V. M. Carvalho 2010; Acemoglu, Carvalho, et al. 2012). This section graphically analyzes the distribution corresponding to the centrality indices.

In **Figure 6**, it is evident that the distributions of the four centrality indices have a high bias towards the right-hand side, indicating the presence of few highly central sectors and a large concentration of sectors that have low centrality indices. This result suggests that these distributions may resemble a power law, and thus corroborate the results of Acemoglu et al. (2012) that heterogeneity is a common characteristic in productive networks.

Figure 6. Distributions of Weighted Centrality Indices



Prepared by: Authors.

Note: The graph indicates the different distributions of the centrality indices, by their histogram and the lilac density curve adjusted by Kernel. The histogram color represents the normalized frequency of the index value; if it is tomato (blue), its value is close to one (zero).

To verify the power law distribution of the centrality indices, the Kolmogorov-Smirnov goodness-of-fit test and Likelihood ratio test are employed.

5.2.1. Kolmogorov-Smirnov goodness-of-fit tests

The Kolmogorov-Smirnov goodness-of-fit test is used to determine whether the centrality indices fit a particular probability distribution, in our case a power law distribution.

These tests performed for each centrality index showed a significance value greater than 0.05, which suggests that the null hypothesis that the centrality indices follow a power law is not rejected, as indicated in **Table 5.**

Table 5. Kolmogorov-Smirnov test

Indices	γ	x-min	KS-stat	p-value
Weighted Grade Centrality	2.33319	1392.038	0.116592	0.856472
Weighted Closeness Centrality	6.342746	0.045070	0.137220	0.779383
Weighted Betweenness Centrality	1.88244	66.0000	0.16034	0.49124
Weighted Alpha Centrality	3.619026	1.01588	0.054956	0.990361

Source: Input-Output Matrix-Central Bank of Ecuador (2019).

Note: The table shows the Kolmogorov-Smirnov goodness-of-fit test. On the rows we have the centrality indices and, on the columns, the values of the exponent of the fitted distribution, the minimum value, the test statistic, and the p-value. If the p-value is less than 0.05, the null hypothesis that the distributions follow a power law is rejected.

This table also shows the value of γ (i.e. the exponent of the fitted power law distribution), and the minimum value from which the power law distribution was fitted. In particular, if the value γ is positive, it indicates that the distribution is skewed to the right.

5.2.2. Likelihood ratio test

The Kolmogorov-Smirnov goodness-of-fit test suggests that, given a minimum value, the distributions of the centrality indices follow a power law. However, this does not rule out the possibility that the distribution has a great probability of belonging to other heavy-tailed distributions. In Tables 4, 5 and 6, we present the comparisons between the power law distribution with the truncated power law, the lognormal distribution, and the exponential distribution, respectively. In each comparison, the Kolmogorov-Smirnov[5], the Anderson-Darling[6], and the Kuiper[7] tests are presented.

These tests analyze the null hypothesis that the power law and other heavy-tailed distribution are equally likely for the data distribution. If the p-value is less than 0.10, it is more likely that the data is adjusted to one distribution more than the other. Hence, if the ratio is positive, the data is more likely to be the first distribution (i.e. power law); however, if the ratio is negative, the data is more likely to be the second distribution.

The comparison between the power law and the truncated power law suggests that both are equally probable for the indices of closeness, betweenness and alpha, at 90% confidence, according to the three tests performed, as shown in **Table 6.** On the other hand, the truncated power law is statistically more likely in the degree centrality index, because it has a negative and significant value in the likelihood ratio, according to the Kolmogorov-Smirnov and Kuiper tests, respectively.

Table 6. Likelihood ratio test comparting the power law and the truncated power law.

Weighted Centrality Indices	**Kolmogorov-Smirnov**		**Anderson-Darling**		**Kuiper**	
	R	**p-value**	**R**	**p-value**	**R**	**p-value**
Degree	-3.6045	**0.007***	-0.8805	0.1845	-1.434	**0.090***
Closeness	-0.169	0.560	-0.095	0.663	-0.580	0.281
Betweenness	-0,155	0.577	-0.699	0.237	-0.699	0.237
Alpha	0.000	0.999	0.000	0.999	0.000	0.999

Source: Input-Output Matrix-Central Bank of Ecuador (2019).

Note: The table shows the probability ratio test between the power law and the truncated power law. On the rows we have the centrality indices and, on the columns, the values of both likelihood ratio and the p-value for the non-parametric Kolmogorov-Smirnov, Anderson-Darling and Kuiper tests. If the p-value is less than 0.10, the null hypothesis that both probability laws are equally probable on the distribution of the data is rejected. The * symbol shows the sectors that have a p-value less than 10%.

[5] The Kolmogorov-Smirnov test analyzes absolute distances.

[6] The Anderson-Darling test analyzes the relative distances.

[7] The Kuiper test analyzes the absolute distances of the maximum differences.

On the other hand, the likelihood ratio test applied between the power law and the lognormal distribution suggests that all the centrality indices are equally probable both in the power law and in the lognormal distribution, through the three tests applied, as observed in **Table 7**. It excludes the betweenness centrality index that better fits a lognormal distribution because it has a negative and significant value in the likelihood ratio, according to the Kolmogorov-Smirnov test.

Table 7. *Likelihood ratio test comparting the power law and the lognormal distribution.*

Weighted Centrality Indices	Kolmogorov-Smirnov		Anderson-Darling		Kuiper	
	R	p-value	R	p-value	R	p-value
Degree	-3,096	0,112	-0,605	0,467	-1,097	0,337
Closeness	-0.103	0.768	-0.218	0.671	-0.824	0.412
Betweenness	-0,999	**0,091***	-0,134	0,748	-0,134	0,748
Alpha	-1.141	0.135	-1.141	0.135	-1.141	0.135

Source: Input-Output Matrix-Central Bank of Ecuador (2019).

Note: The table shows the probability ratio test between the power law and the lognormal distribution. On the rows we have the centrality indices and, on the columns, the values of both likelihood ratio and the p-value for the non-parametric Kolmogorov-Smirnov, Anderson-Darling and Kuiper tests. If the p-value is less than 0.10, the null hypothesis that both probability laws are equally probable on the distribution of the data is rejected. The * symbol shows the sectors that have a p-value less than 10%.

Finally, the significant and positive likelihood ratio between the power law and the exponential distribution provides evidence that the alpha and betweenness indices better fits a power law distribution, using the Kolmogorov-Smirnov and Kuiper tests. In contrast, the degree and closeness centrality indices are equally adjusted to both distributions given that the p-value is larger than 0.10 in the three tests applied, as shown in **Table 8**.

Table 8. Likelihood ratio test comparting the power law and the exponential distribution.

Weighted Centrality Indices	Kolmogorov-Smirnov		Anderson-Darling		Kuiper	
	R	p-value	R	p-value	R	p-value
Degree	4,074	0,477	0,709	0,758	1,110	0,717
Closeness	-0.149	0.801	-0.101	0.419	-0.654	0.167
Betweenness	16,084	**0,004***	7,796	0,096	7,896	**0,096***

Alpha	8.031	**0.079***	8.031	**0.079***	8.031	**0.079***

Source: Input-Output Matrix-Central Bank of Ecuador (2019).

Note: The table shows the probability ratio test between the power law and the exponential distribution. On the rows we have the centrality indices and, on the columns, the values of both likelihood ratio and the p-value for the non-parametric Kolmogorov-Smirnov, Anderson-Darling and Kuiper tests. If the p-value is less than 0.10, the null hypothesis that both probability laws are equally probable on the distribution of the data is rejected. The * symbol shows the sectors that have a p-value less than 10%.

6. Conclusions

The objective of this study was to analyze at sectoral level the Ecuadorian productive network using indicators based on network theory. Its main contribution is to provide details on the role played by the sectors, through centrality indices and power law. Theoretically, these features are mainly important to identify the most influential sectors for the diffusion of productivity shocks, the propagation of cascade effects and the generation of macroeconomic fluctuations.

According to the results, the sectors of wholesale and retail trade (54), transport (58), and professional activities (64) are the most influential in the Ecuadorian economy, because they prevail in the four centrality indices. Therefore, these sectors are capable of commercializing high amounts of purchases and sales (degree), have a strategic place to carry out efficient transactions (betweenness), increase their production for other economic activities (alpha), and are closer to their final consumers (closeness). Furthermore, the distribution of the productive sectors according to the centrality measures follow a power law. This characteristic shows that the participation of the sectors in the productive network is highly asymmetric, that is, there are few sectors with high centrality and many sectors with low centrality. According to the theory of shock diffusion, the sectors mentioned above can predetermine the activity of the entire productive network, because a microeconomic shock to these sectors could spread “downstream” cascade effects throughout the intersectoral links and generate aggregate fluctuations, as argued by Acemoglu et al. (2012), Carvalho et al. (2016) and Gabaix (2016).

Finally, this study shows the empirical importance of network theory tools for ex-ante analysis, as they allow policy makers to identify key features about the organization and interrelation between industries in the production network. Thus, the corresponding authorities could adequately invest in the productive sectors that generate dynamism and economic growth. Given the findings for

Ecuador's economy, the government could reinforce policies that protect highly central sectors from adverse external shocks or policies that increase their productivity.

For example, the professional activities sector (64) requires policies focused on increasing the national research and development budget, which will open space for the creation of new technology-based companies. In addition, the study plans for education should be reoriented depending on the market requirements to obtain a highly specialized and competitive professional training at a national and international level.

For the wholesale and retail trade (54), it is suggested to reduce taxes and business credit rates, which can promote greater investment in new ventures. For the transport and storage sector (58), access to investment should be facilitated for the acquisition of vehicles and an adequate infrastructure that allows the transfer of products between different suppliers and consumers. Government-administered grants must be fuel-focused, as fuel is an inelastic good. Given that, transportation has a high centrality, therefore a decrease in subsidies will cause an increase in the costs of products, that will spread throughout the production network, ultimately affecting the price of the final consumer goods.

Given the heterogeneous structure of the Ecuadorian productive network, the chains of those most fragile sectors should be strengthened, through a public policy that encourages vertical cooperation with the sectors of greater centrality, which are found in clusters D and E. For example, the R&D implementation aims to take advantage of complementary resources, transfer information about markets and technology, and the needs of users. Furthermore, it would be interesting to extend this study towards a horizontal cooperation analysis, as long as microeconomic data (i.e. at the company level) are available.

To conclude, some possible recommendations are presented for a possible extension of this analysis. Econometric models can be used to quantify upstream and downstream effects caused by a shock to a core industry. Another alternative is the dynamic analysis which measures the significance and the effect of variables such as employment, taxes, technology, and intermediate consumption in the total added value of the sectors. The detection of communities in the productive network is an analysis that provides information on patterns that are not so visible, such as, detecting highly connected communities that do not allow the dissemination of a productive shock, but that affects only that community. Finally, spatial analysis is one of the alternatives that can allow us to know the integration between the central, regional, and local levels, with the aim of improving the productivity of the economic system.

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8. Appendix

Appendix A. List of the productive sectors with the identifier and Chenery and Watanabe categorization.

Id	Sector	CW categorization
1	Growing of banana, coffee, and cocoa	Base
2	Growing of cereal	Base
3	Growing of flowers	Isle
4	Growing of vegetables, melons, fruits and tubers	Isle
5	Growing of oleaginous and industrial crops	Base
6	Support activities for crop production	Isle
7	Raising cattle, other animals; animal products; and support activities	Key
8	Silviculture, timber extraction and other forestry activities	Isle
9	Aquaculture and shrimp fishing	Key
10	Fishing (except shrimp)	Isle
11	Aquaculture (except shrimp)	Motor
12	Extraction of crude petroleum and natural gas	Key
13	Support activities for petroleum and natural gas extraction	Isle
14	Mining of metal ores	Isle
15	Mining of non-metallic ores and support activities for other mining and quarrying	Isle
16	Processing and preserving of meat	Motor
17	Processing and preserving of shrimp	Motor
18	Processing of fish and other processed aquatic products	Motor
19	Conservation of aquatic species	Motor
20	Manufacture of vegetable and animal oils and fats	Motor
21	Manufacture of dairy products	Motor
22	Manufacture of grain mill products	Isle
23	Manufacture of bakery products	Motor
24	Manufacture of noodles and similar farinaceous products	Motor
25	Manufacture and refining of sugar	Motor
26	Manufacture of cocoa, chocolate and sugar confectionery	Motor
27	Manufacture of prepared animal feeds	Isle
28	Manufacture of coffee	Motor
29	Manufacture of other food products	Motor
30	Manufacture of alcoholic beverages	Isle
31	Manufacture of non-alcoholic beverages	Motor
32	Manufacture of tobacco products	Isle
33	Manufacture of threads, yarns; fabrics and clothing	Key
34	Manufacture of wearing apparel	Motor
35	Manufacture of leather, leather products and footwear	Motor
36	Manufacture of wood and of products of wood	Key
37	Manufacture of paper and paper products	Base

38	Manufacture of refined petroleum and other products	Base
39	Manufacture of basic chemicals, fertilizers, and primary plastics	Isle
40	Manufacture of other chemicals	Isle
41	Manufacture of rubber products	Isle
42	Manufacture of plastic products	Base
43	Manufacture of glass, refractory products, and ceramics	Isle
44	Manufacture of cement, articles of concrete and stone	Motor
45	Manufacture of basic metals	Key
46	Manufacture of fabricated metal products, except machinery and equipment	Isle
47	Manufacture of machinery and equipment	Motor
48	Manufacture of transport equipment	Isle
49	Manufacture of furniture	Motor
50	Manufacturing industries n.e.c.	Base
51	Electric power generation, transmission, and distribution	Key
52	Water collection, treatment, and supply	Isle
53	Construction of buildings	Isle
54	Wholesale and Retail; including trade of motor vehicles and motorcycles	Base
55	Maintenance and repair of motor vehicles	Isle
56	Accommodation	Motor
57	Food and beverage service activities	Motor
58	Transport and warehouse	Base
59	Postal and courier activities	Motor
60	Information and communication	Motor
61	Financial service activities	Base
62	Insurance plans, except social security	Key
63	Real estate activities	Base
64	Professional, technical, and administrative activities	Base
65	Public administration, defence; compulsory social security	Isle
66	Private teaching services	Isle
67	Public (non-market) education services	Isle
68	Private health and social services	Isle
69	Non-market health and social services	Isle
70	Association services; entertainment; cultural and sport activities	Isle

Source: Central Bank of Ecuador (2019). Input-Output Matrix
Note: The list shows the identifier of the 70 productive sectors with their respective name according to the International Standard Industrial Classification (ISIC).

Appendix B. The top 7 industries with the greatest centrality.

A) Degree Centrality (millions of dollars)

Id	Sector	Index	Categorization CW	Clustering by centrality
64	Professional and administrative activities	$ 11,973.8	Base	E
54	Wholesale and retail	$ 11,213.3	Base	E
58	Transport and storage	$ 9,768.6	Base	E
53	Construction	$ 7,847.6	Isle	D
12	Extraction of crude oil and natural gas	$ 4,970.7	Key	D
61	Financial services activities	$ 4,715.9	Base	D
51	Generation, capture and distribution of electrical energy	$ 4,642.1	Key	C

B) Closeness Centrality

Id	Sector	Index	Categorization CW	Clustering by centrality
64	Professional and administrative activities	0.0785	Base	E
58	Transport and storage	0.0733	Base	E
38	Manufacture of refined petroleum and other products	0.0685	Base	D
54	Wholesale and retail	0.0680	Base	E
61	Financial services activities	0.0669	Base	D
12	Extraction of crude oil and natural gas	0.0645	Key	D
13	Activities that support oil and natural gas extraction	0.0630	Isle	C

C) Betweenness Centrality

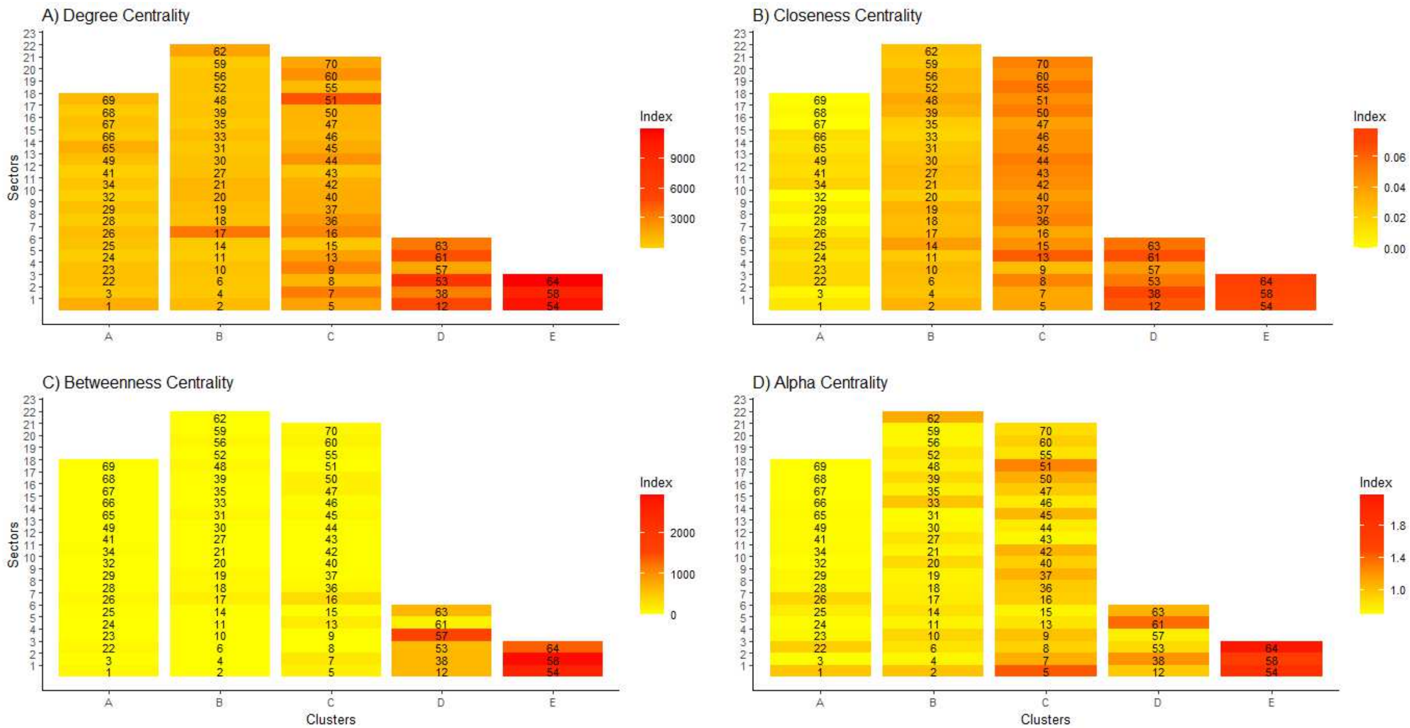
Id	Sector	Index	Categorization CW	Clustering by centrality
58	Transport and storage	2910	Base	E
54	Wholesale and retail	2524	Base	E
57	Food and beverage service	1523	Motor	D
64	Professional and administrative activities	1351	Base	E
63	Real estate activities	653	Base	D
38	Manufacture of refined petroleum and other products	645	Base	D
12	Extraction of crude oil and natural gas	642	Key	D

D) Alpha Centrality

Id	Sector	Index	Categorization CW	Clustering by centrality
64	Professional and administrative activities	7.8151	Base	E
54	Wholesale and retail	5.7642	Base	E
58	Transport and storage	4.3239	Base	E
5	Oilseed and industrial crops	3.2113	Base	C
61	Financial services activities	2.9428	Base	D
51	Generation, capture and distribution of electrical energy	2.5866	Key	C
38	Manufacture of refined petroleum and other products	2.3488	Base	D

Source: Input-Output Matrix-Central Bank of Ecuador (2019).
Note: The table represents the 7 sectors with the lowest weighted centrality indices
proposed by Chenery and Watanabe (1958) is indicated

Appendix C. Clusters according to the centrality indices.



Note: The figure shows the configuration of five groups detected by clustering of k-means and the conformation of their sectors according to the indexes of degree, closeness, betweenness and alpha centrality. The color of the stacked bars represents the centrality index value, if the color is red (yellow) the higher (lower) the index value.