Assessing productive structures in Brazil with dynamic input–output networks

Abstract

A main limitation of input–output models is that their results are based on static time periods. To improve this analysis, we propose a different view based on dynamic input–output networks, and apply it to evaluating productive structures in Brazil over time. We use Brazilian matrices from the World Input–Output Database for the period 1995–2011. The main results show two different macroeconomic effects: (i) possible positive impacts of macroeconomic policies and higher commodity prices on increased network connectivity between 2002 and 2003; and (ii) the negative influence of the 2008 crisis, which resulted in decreased network connectivity. In the first period, the beginning of the commodity cycle associated with new macroeconomic policies may have positively influenced, in part, Brazil's intersectoral dynamics. In contrast, in 2009, the deleterious effects of the global economic crisis of 2008 may have contributed to a reduction in intersectoral relations in Brazil.

Keywords: Brazilian economy; input–output network; time-varying graph.

1. Introduction

Econophysics is the use of complex systems in economic studies (Carbonne et al., 2007; Jovanovic and Schinckus, 2017; Mantegna and Stanley, 1999; Pereira et al., 2017; Schinckus, 2013). It is an approach that has advanced both the identification of economic problems and attempts to solve them. According to Pereira et al. (2017), network theory is among the subareas that have contributed to econophysics. Schweitzer et al. (2009) defined the importance of network theory to the economy, since in networks, it is possible to study properties such as time and space, structure identification, and systemic feedback, providing a novel approach to assessing the productive structure of countries or regions.

The seminal study of network theory and production was conducted by Solow (1952), who analyzed aggregate fluctuations. Bak et al. (1993) later showed the importance of inputs and the supply chain in diffusing shocks between aggregate sectors. In the last two decades, interest in network theory and improvements in computation have enabled the development of several network analysis methods and the discovery of new network properties.

In the input–output (IO) field, a recent advance that has allowed hypotheses to be more flexible and has reinforced results is integration with other models, such as linear programming (Hristu-Varsakelis et al., 2012; San Cristóbal, 2012; Souza et al., 2016), econometric models (Kim et al., 2015; Kratena and Temursho, 2017) and complex networks (Carvalho and Gabaix, 2013; Cerina et al., 2015; Tsekeris, 2017). Specifically, Acemoglu et al. (2012) and Carvalho (2010) have used network theory to analyze the problem of aggregate fluctuations in macroeconomics. Cerina et al. (2015), using a world IO database, analyzed the inter-industry relations of several countries through calculations of PageRank centrality and community coreness. In addition, Río-Chanona et al. (2017) evaluated trade relations among 40 economies, and found a strong correlation between the three major economies (United States, China and Germany), indicating a high centrality between trade relations.

Recent research involving trade relations between several countries has used networks that emphasize the role of centrality (Blöchl et al., 2011; Xing et al., 2017) and country-specific assessments (He et al., 2017; Tsekeris, 2017; Xu et al., 2011). It is important to highlight that other studies have also analyzed production, but not necessarily using IO matrices (Atalay et al., 2011; Hidalgo and Hausmann, 2009; Ohnishi et al., 2010; Xiao et al., 2017).

Integrating IO models into network theory is even more interesting when applied to complex productive structures, as seen in Brazil. Moreover, results improved considerably if the database used covers a long period of time, because it can account for important factors, such as structural and governmental changes. This study intends to develop an analysis of dynamic

IO networks to evaluate the evolution of the Brazilian productive structure, considering the varying sector relationships over time. As far of our knowledge, this type of approach has never been applied before. Thus, it is possible to measure the impacts of economic events such as financial crises or macroeconomic policies on the properties of the networks or the interconnection between economic sectors. For this, we use a network analysis of Brazilian IO matrices for the period 1995–2011.

The main contributions of this paper are: (i) a novel method for evaluating productive structures; (ii) an assessment of the macroeconomic policies introduced by different governments over time; and (iii) a contextualized analysis of strongly linked sectors. All of these topics could be generalized to any other country. The remainder of this paper is organized as follows. The next section presents fundamental concepts of the IO model and network. The third section explains our proposed method, and the fourth contains our main results and discussion. The last section includes our final remarks and future research agenda.

2. Fundamental concepts of input–output models and networks

2.1. The input–output model

The IO model, developed by Leontief (1966), represents a snapshot of the economy at a given moment (Miller and Blair, 2009). More specifically, according to Prado (1981), an IO model is a linear production model in which an economic system is simplified into matrices of intersectoral flows of inputs and outputs. In summary, traditional IO analysis considers a system of linear equations, where each sector combines a set of inputs from other economic sectors to produce a given output. We must obtain a vector x_j that indicates the total production value of each sector j. For that, we use the equation $x = Bf$, where B is a Leontief inverse matrix and f is the final demand vector.

The Leontief inverse matrix is calculated by the equation $B = (I - A)^{-1}$, where A is the technical coefficient matrix given by $A = a_{ij} = \frac{z_{ij}}{x_j}$ and z_{ij} is the trade between sectors i and j. Each element of the Leontief inverse matrix b_{ij} should be interpreted as the total output of sector i that is required for producing a final demand unit of sector j. Once obtained, we interpret the IO matrices (supposing we have T matrices, one for each time $t = 1, 2, 3, \ldots, T$) as weighted matrices and use them to build IO networks that vary over time. An IO network can describe the connection weights between sectors of the economy.

2.2. Graphs and networks

In general, a nondirected graph or network consists of a set of vertices and a set of edges that connect the vertices. Mathematically, we can use the following notation to describe graph $G = (V, E)$, where V is a finite and nonempty set of vertices, and E is a set in which binary relations on V are defined. Thus, an edge can connect one or two vertices. Nevertheless, when an edge is directed, we have an arc or an ordered pair of vertices. Our IO networks are directed networks. In this case, we have a directed graph or digraph $G = (V, A)$, where V is a finite and nonempty set of vertices, and A is a set of ordered pairs of vertices of V. A weighted and directed network can be represented by an $n \times n$ cost matrix $W = \{w_{ij}\}$. If $w_{ij} = 0$, there is no directed connection between *i* and *j*, but a directed connection between *j* and *i* may exist, if $w_{ji} \neq 0$. The weighted and directed IO networks used in this paper are composed of positive weights; thus, $w_{ij} > 0$, $\forall\, i, j$. According to Carvalho and Salehi (2018, p. 3):

> The input-output linkages between various industries can alternatively be represented by a weighted and directed graph on *n* vertices. Each vertex in this graph — which we refer to as the economy's production network —corresponds to an industry, with a directed edge with weight $a_{ij} > 0$ present from vertex *j* to vertex *i* if industry *j* is an input-supplier of industry *i*.

Due to the lack of standardization in the formalization of some network properties, we present a short glossary of properties used in this paper:

- The number of vertices $n = |V|$ is given by the cardinality of the set of vertices.
- The number of arcs $m = |A|$ is given by the cardinality of the set of arcs.
- The degree of vertex i is denoted by k_i and consists of the number of edges connecting vertex i.
- The average degree of an undirected network is given by $\langle k \rangle = \frac{1}{n}\sum_{i=1}^{n} k_i$. For directed networks, we calculate the average of the input and output degrees.
- Let us consider that $\Gamma(i)$ is the neighborhood of vertex i. The weighted degree of vertex i is given by the sum of the weights of all in-or-out arcs connected to vertex i, $k_{wi} = \sum_{j \in \Gamma(i)}[w_{ij} + w_{ji}]$.
- The weighted average degree is given by $\langle k_w \rangle = \frac{\sum_{i=1}^{n} k_{w_i}}{n}$
- The average clustering coefficient of the network vertices is $C = \frac{1}{n}\sum_{i=1}^{n} C_i$. C_i is the clustering coefficient of vertex i and measures the proportion of existing edges between neighbors of vertex i, denoted by E_i. The maximum possible number of edges is $\frac{n(n-1)}{2}$.
- Average minimal path length is the average geodesic distance and is given by $L = \frac{1}{n(n-1)}\sum_{i \neq j} d(i,j)$, where $d(i,j)$ is the shortest path between vertices i and j.
- The diameter is the longest shortest path between two vertices in a network, denoted by max $d(i,j)$.
- The density of a directed network is given by $\Delta = \frac{m}{n(n-1)}$ and consists of the total existing arcs m, divided by the maximum possible number of arcs $n(n-1)$.
- Global efficiency is defined by Latora and Marchiori (2012) as $E(G) = \frac{1}{n(n-1)}\sum_{i \neq j \in G}\frac{1}{d(i,j)}$, where $d(i,j)$ is the average minimal path length between i and j. Local

efficiency is defined as $E_{local} = \frac{1}{n}\sum_{i\in G} E(G_i)$, where $E(G_i)$ is the efficiency of the local subgraph G_i (i.e. neighborhood of i) with $i \notin G_i$.

In order to avoid any confusion with the use of variables, we recall the use of L as a variable of the average minimal path length and B as Leontief inverse matrix.

2.3. Time-Varying Graphs and Networks

Although the terms temporal networks, dynamic networks, and time-varying graphs (TVGs) consist of different concepts, we often find them used synonymously. For example, according to Nicosia et al. (2013) TVGs or graphs that evolve over a specific period are also called dynamic networks, in which edges or arcs appear and disappear over time for a set of vertices. This kind of network shows relationships that change over time; we can therefore capture the dynamics of the network and model them using "time-ordered sequences of graphs over a set of nodes" (Nicosia et al., 2013).

We use the formalism for TVGs proposed by Casteigts et al. (2012). A TVG is described as $\mathcal{G} = (V, A, \mathcal{T}, \rho, \zeta)$, where V is the set of vertices, A is the set of arcs connecting pairs of vertices of V, $\mathcal{T}$ is the time interval used to analyze the system, ρ is the presence function $\rho: A \times \mathcal{T} \rightarrow 0, 1$, and ζ is the latency function that indicates the time required to form arcs.

Within this context, $\mathcal{G}$ is the time-varying IO network $\mathcal{G} = (V, A, \mathcal{T}, \rho, \zeta)$, where $V = \{v_1, v_2, \dots, v_n\}$ consists of the set of sectors of the Brazilian productive structure based on IO models; $A = \{a_1, a_2, \dots, a_m\}$ is the set of IO relationships between Brazilian economic sectors at a given time; $\mathcal{T}$ is the time interval starting in 1995 and ending in 2011 (i.e. $|\mathcal{T}| = 17$), $\mathcal{T} = \{t_1, t_2, \dots, t_i, t_{i+1}, \dots, t_{|\mathcal{T}|}\}$; ρ indicates the existence or absence of the IO relationship between two sectors at a given time ($t_i \in \mathcal{T}$) and the IO relationships that can be removed or included according to the use of a filter associated with the arc weights; in this work, we ignore latency function ζ because the IO arcs possess null latency. Finally, it is important to highlight that all sectors are present during time interval $\mathcal{T}$.

A filter is just a criterion adopted in order to leaving the network less polluted and improve the analysis. Economically speaking, we are taking into account the most important relationships between sectors. Otherwise, the network would have all possible arcs.

Because TVG can describe several different scenarios, from transport networks (Santos et al., 2018) to neural networks (Rosário et al., 2015), we have used its formalization to model and analyze the dynamics of the Brazilian IO network. Some works, such as Holme and Saramäki (2012), present a variety of relevant examples of temporal networks.

3. Materials and proposed methods

In this work, we use annual Brazilian IO matrices. Fig 1 summarizes the general framework of the proposed method, which consists of five processes. The processes will be described in detail below:

- Obtain the weight matrices
- Organize the data
- Statistically analyze the weights
- Build the (time-varying) weighted networks
- Analyze the networks

<Figure 1>

The first process in the general framework for building and analyzing a time-varying weighted network is obtaining the weight matrices. We use the annual Brazilian IO matrices obtained from the World Input–Output Database (Timmer et al., 2015) for the period 1995–2011 with 35 economic sectors [http://www.wiod.org/database/wiots13]. We have aggregated

Sector 35, “Private Households with Employed Persons,” into Sector 34, “Other Community, Social, and Personal Services”. The main advantage of this database is the availability of compatible annual matrices for a group of 40 countries during this period. In our case, each year is equivalent to an instance of time *t*.

The second process is organizing the data. Here, we consider the statistical and network tools used to perform our analysis and build the IO networks, from yearly IO matrices for the analysis period.

We define the filter to be used in IO networks in the third process based on a statistical analysis of the weights.

In the fourth process, we build the (time-varying) weighted networks, using the IO matrices mentioned in the second process.

Finally, in the fifth process, we carry out the network analysis to find the network properties and characterize the topology of Brazilian economic sectors given economic and political events.

3.1. Statistical analysis of weights

An IO Network is associated with a specific IO matrix. In this context, for each year, we have an $n \times n$ IO matrix with which we build a time varying network based on the annual tables.. Let us consider that each static IO network is nonsymmetric (i.e., $w_{ij} \neq w_{ji} \geq 0$). Although there are loops in the IO network, we do not consider them. That is we exclude intrasectoral relations (i.e., all elements on the main diagonal of each matrix). In addition, it is important to highlight that the weighted and directed IO networks used in this paper are composed of positive weights, (i.e., $w_{ij} > 0$).

Various approaches have been used to establish a filter, i.e., the edges or arcs that are considered in network analysis. For example, Carvalho (2010) summed the total transactions of a single sector and considered only relations greater than 1%, whereas Blöchl et al. (2011) considered transactions greater than 1 billion and 500 million USD, respectively. Acemoglu et al. (2012) and Tsekeris (2017) used the mean and the mean plus one standard deviation, since they believed that standard deviation would capture the volatility or aggregate shocks in the economy.

In our case, we chose to adopt the mean plus one standard deviation as this would discard mostly irrelevant information. In Fig 2, we show a histogram of 19,074 weights (i.e., the Leontief inverse coefficients between sectors i and j for $i \neq j$) of Brazil's IO matrices. As indicated with arrows in Fig 2, we found $\langle w \rangle = 0.01964$ ($\sigma = 0.03125$) and the $\langle w \rangle + 1\sigma \approx 0.051$. For this set of data, we use the $\langle w \rangle + 1\sigma$ as a filter to be applied to select the arcs used in network analysis. Thus, we account for the most relevant data to analyze and assess the macroeconomic shocks from a dynamic perspective.

<Figure 2>

The adopted criterion of using the average weight plus one standard deviation (i.e. $\langle w \rangle + 1\sigma$) of the links as pruning filter for the arcs is well founded in the literature (e.g. Tsekeris, 2017), and it is also supported by an analysis over time (Fig 3). We see that there is not much fluctuation and it seems reasonable to argue that this is evidence that it is not necessary to use some alternative "varying threshold" approach. As we can see in Fig. 3, the data variability is small from year to year.

<Figure 3>

3.2. Building the aggregate static IO network

In Fig 4, the aggregate static IO network is shown both without (Fig 4a) and with (Fig 4b) the filter $w_{ij} \geq 0.051$. As commented, we consider the average of the all Leontief Inverse matrix's elements for all time windows (17 years). We observe a general pattern related to the connection strength of some sectors of the economy, which we discuss later.

<Figure 4>

3.3. Building the time-varying IO network

To analyze the dynamics of the IO network, we consider three criteria: (i) the establishment of a filter based on our statistical analysis (previously discussed); (ii) the inclusion of temporal data, to analyze each static IO network separately; and (iii) the analysis of the dynamics of the IO network. We have also carried out topological analysis for each static IO network.

For each instance of time t, we have an $n \times n$ matrix (Fig 5). In Fig 5a, we show the filtered seventeen static IO networks, and in Fig 5b, we present the aggregated filtered static network. In both figures, we have applied the filter $w_{ij} \geq 0.051$ to select the arcs for use in the network analysis. Temporal data were included during data organization and building the (time-varying) weighted networks, i.e., the second and fourth processes in the proposed method, as explained in Section 3, allowing us to analyze each static IO network separately and to study the dynamics of the IO network.

<Figure 5>

4. Results and discussion

Before presenting the results it is important to characterize economically the analyzed period (1995-2011). The 1990s were marked by many profound changes in the Brazilian economy, including trade and financial openness at the beginning of the decade, the privatization of public companies, and price stabilization in 1994, ending with a new macroeconomic policy resulting from an exchange rate crisis (Moreira and Ribeiro, 2013). In the 2000s, neoliberalism began to weaken, and public investments in strategic infrastructure sectors resumed. Furthermore, income-transfer-based social programs, in conjunction with other measures, had a positive impact on decreasing regional inequalities in Brazil (Ribeiro et al., 2018; Silveira-Neto and Azzoni, 2011; 2012).

To facilitate our analysis, we present our results from two perspectives: (i) macroeconomic, identifying the behavior of the network properties over time; and (ii) sectoral, through preeminence analysis that allows us to identify poles over time, i.e., the sectors that represent the strongest and most important trade relations or linkages in the Brazilian productive structure.

Fig 6 shows the behavior of the network properties over time. It is possible to see a change, first during 2002–2003, for variables such as density, weighted average degree and global efficiency.

The weighted average degree indicates the influence and prestige of the Brazilian economic sectors. In a directed network, the concepts prestige and influence refer to the quantity of choices received and choices made, respectively. In the input-output networks, prestige is associated with the receipt of inputs and the influence on the supply of inputs. In 2002 and 2005, for instance, we observed increases in this index, which means that sectors have become more dependent on each other.

Global efficiency, in turn, can be understood as the speed with which information (i.e. input or output) goes from one Brazilian economic sector to another. This property measures how much the Brazilian economic sectors efficiently supply inputs to other sectors (or “transport information”). In the years of 2002 and 2004, the increase of these indicators may be associated with the commodities cycle.

The average clustering coefficient behavior indicates that, from a general point of view, the increases occurred (2004-2008) are related to the influence that the Brazilian economic sectors exert on each other (local neighborhoods) from each sector analyzed in terms of supplied inputs.

The average minimum paths *(L)* indicate how close the Brazilian economic sectors are. The decrease in L and the increase in density suggest an “approximation” among the sectors, which could be related to the emergence of strategic arcs (important economic relationship). In other words, sectors can interact with each other without the need for many intermediaries, i.e., the Brazilian economy became more conducive to diffusion processes since its sectors became more connected.

In 2004, there was a reduction in density, weighted average degree and global efficiency. To explain this drop is important to mention that President Lula's government began in 2003. His political position provoked a general distrust on the ability of the new government to honor the pre-established commitments such as the payment of external debt. Giambiagi and Villela (2005) argue that to contain speculation in the financial market, President Lula has taken some economic adjustment measures, especially the increase of the interest rate and the reduction of public spending. These measures adopted in 2003 possibly impacted sectoral relations in the following years, especially in 2004. This discouragement of trade relations between sectors contributed to the reduction of network connectivity measured through the analyzed indicators.

In 2009, there was also a reduction in average degree, diameter, and local efficiency. With respect to local and global efficiencies, we observe a network tendency to a small-world topology. This means that the network tends to be sparse and connected, having a high agglomeration coefficient and a reduced average minimum path (Watts and Strogatz, 1998). In addition, the input-output network tends to be more efficient in transporting information (inputs). We can assume that in 2003–2009, average degree, diameter, and average minimum path length, the static and aggregate IO networks are more interconnected, for reasons we discuss below.

Possible influences on networks properties for the period between 2003 and 2009 include the macroeconomic policies adopted during Fernando Henrique Cardoso's second term, such as adopting a floating exchange rate, inflation targets and privatization. They could have contributed to an increase in the network interconnection. This pattern is observable from the density behavior since the number of vertices is fixed at 34, the density in each time window indicates the importance of Brazilian economic sectors as suppliers or demanders of inputs (Fig 6a). These policy mechanisms may have positively impacted intersectoral trade relations, due to the greater degree of trade liberalization in the Brazilian economy that began in the 1990s. In addition, they provided greater macroeconomic stability during the period analyzed and increased incentives for several sectors (Fig 6b).

These changes in network properties (Fig 6) may also be associated with what was known in the Brazilian economy as the "commodity cycle." This cycle, delimited between 2002 and 2009, was characterized by the continuous rise in commodity prices in the international market. Since Brazil has historically been an agro-exporting country, this rise in prices was followed by an upturn in the economy, as reflected in the increase in trade relations between several network sectors, mainly based on the rise in average levels (Fig 6b). It is worth noting that, according to Cepal (2014), commodity-producing activities usually have productive enclaves and multiplier effects on other sectors are reduced. That is, the positive effects on the Brazilian economy could have been much larger if the external shock influenced more interconnected sectors, as is the case, for example, with industrial activities.

The increase in demand from the Chinese market was one of the main causes of the commodity cycle. For these reasons, between 2005 and 2011, commodity exports contributed to a real growth of 0.7% to the Brazilian Gross Domestic Product (Sessa et al., 2017). The economic effects of these exports in the Brazilian economy involve important micro- and macroeconomic aspects, such as changes in relative prices and an exchange rate depreciation. Considering the spatial heterogeneity of Brazilian development (one of the five regions, Southeast, accounts for 54% of Brazilian GDP in 2015), the expansion and retraction of commodity exports altered the general structure of relative prices within the economy.

<Figure 6>

After 2009, on the other hand, we observe a drop in all network properties analyzed (Fig 6). The greatest reduction was in relation to the average cluster coefficient, global efficiency, and local efficiency (Figs 6c and 6f). A likely explanation for this behavior may have been the 2008 global economic crisis. According to Borghi (2017), this crisis "severely affected Brazil's growing economy at the end of 2008 and especially in the following year." Industrial production and GDP in several countries declined rapidly in the last quarter of 2008, which may have negatively influenced relations between various sectors of the Brazilian economy. In that year, the Brazilian economy registered a decrease of 0.13% in GDP. Moreover, Borghi (2017) argues that the Brazilian industrial sector was the most affected sector and because it accounts for the most links in the economy, this could explain the results observed after 2009. The behavior of the network is not homogeneous among the different sectors. Therefore, another possible analysis is the identification of the strongest intersectoral relations of the Brazilian productive structure during the period 1995-2011. Fig 4b reveals the above-average trade ratios considering all the elements of the Leontief inverse matrices ($\mathrm{w_{ij}} \geq 0.051$). In addition, Fig 7 shows the strongest trade relationships with above-average values ($0.2015 \leq$

$w_{ij} \leq 0.3362$), considering the average of all the elements of the 17 Leontief inverse matrices. In visual terms, these relationships are represented by thicker arcs between economic sectors.

<Figure 7>

In Fig 7, we clearly observe the formation of three distinct sectorial complexes: (i) food; (ii) petrochemical; and (iii) machinery and metal. The food complex has strong links with the Agriculture, Hunting, Forestry, and Fishing; Food, Beverage, and Tobacco; and Hotel and Restaurant sectors. Although the petrochemical complex shows strong trade relations, they occur between two groups of independent sectors: (i) Mining and Quarrying and Coke, Refined Petroleum, and Nuclear Fuel and (2) Chemicals and Chemical Products and Rubber and Plastics. It is important to emphasize that the first sector aggregates oil extraction activities, whereas the other activities are manufacturing-related. Finally, Fig 7 also reveals a strong trade relationship between Basic Metals and Fabricated Metal and Machinery, "not elsewhere classified" (Nec). Of the three sectorial complexes mentioned above, the largest are Hotels and Restaurants (Group i); Coke, Refined Petroleum, and Nuclear Fuel and Rubber and Plastics (Group ii); and Machinery, Nec (Group iii).

In Fig 8, we highlight the behavior of the most important sectors based on the strongest linkages in the static IO aggregate networks (Fig 7), considering the weighted degree This metric can be interpreted as weighted intersectoral relations, capturing the weight of trade relations between sectors.

<Figure 8>

Fig 8 illustrates a completely different dynamic between these nine sectors over time. Three groups are defined based on weighted degree: (i) Rubber and Plastic, Machinery, Nec, and Hotels and Restaurants, which for which the degree varies between 0 and 0.6 in most periods; (ii) Chemicals and Chemical Products, Agriculture, Hunting, Forestry, and Fishing, Coke, Refined Petroleum, and Nuclear Fuel, Basic Metal and Fabricated Metal, and Food, Beverage, and Tobacco, which have a weighted degree varying on average between 0.7 to 1.2; and (iii) Chemicals and Chemical Products with a weighted degree greater than 1.2 for most of the period.

Economically speaking, the weights of the chemical sector’s trade relations (linkages) were the strongest in the Brazilian economy between 1999 and 2008. Moreover, this sector peaked in 2003 and successively dropped until 2011. Mining and Quarrying, however, is the only sector that has an increase in its weighted degree after the international crisis. It is important to highlight that part of these results are due to price effects once our tables are in current prices. Dietzenbacher and Temurshoev (2012) have shown for Denmark economy that current and constant prices methods provide very similar results in an aggregate level such as gross output and employment. In a sectoral level, however, the differences were larger.

An interesting observation is that the Mining and Quarrying; Food, Beverage, and Tobacco; Coke, Refined Petroleum, and Nuclear Fuel; Chemicals and Chemical Products; and Basic Metals and Fabricated Metal sectors, which showed the highest-weighted degrees, were classified as key sectors in all years. This classification is based on the Hirschman–Rasmussen indices. In general, for an industry to be classified as a key sector, it must simultaneously display backward and forward linkages greater than one. To learn more, see Miller and Blair (2009). They had above-average intersectoral supply-and-demand relationships. In a way, this result serves as a robustness test for the proposed model.

5. Conclusions

To evaluate the Brazilian productive structure between 1995 and 2011, we have developed an integrated network IO model using annual IO matrices composed of 34 economic sectors. The main contribution of this method is its ability to capture the structural endogenous or exogenous effects on the productive structure of a given country or set of countries. Such effects are measured in an integrated manner given the connectivity of economic agents via trade relations. In fact, the analysis of IO network dynamics is one of the main strengths of this work, since it relaxes one of the most restrictive hypotheses of the IO models (i.e., static analysis), and enables the assessment of productive structures over time.

Interpretations based on the networks properties, although qualitative, are supported by quantitative values. Measures of network properties during the analyzed period are sensitive to variations in political and economic changes. For instance, the new macroeconomic regime in 1999 and the strengthening of Lula's social policies in the early 2000s.

We found two main distinct macroeconomic effects on the Brazilian economy during two periods: (i) possible positive impacts of the macroeconomic policies of Fernando Henrique Cardoso’s second term as president and increasing commodity prices in the increase in network connectivity between 2002 and 2003; and (ii) the negative influence of the 2008 crisis, shown as a decrease in network connectivity. Thus, we conjecture that, in the first period, the macroeconomic policies initiated in the late 1990s associated with the beginning of the commodities cycle had a positive influence on the dynamics of the country's intersectoral relations. On the other hand, in 2009, the fall in the intensity of these relations may be associated with the deleterious effects of the global crisis.

The sector results revealed three groups whose trade relations increased throughout the analysis period: food, petrochemical and metals, and machinery. The Coke, Refined Petroleum, and Nuclear Fuel sector, in particular, has experienced intensified trade relations since 2003, which can be explained by the greater targeting of investments in this area, a policy conducted by the Lula Government, particularly for the Petrobras company.

However, it is worth mentioning that part of these results is due to price effects once our tables are in current prices. Between 2003 and 2011, for instance, the annual inflation average rate in Brazil was 5.9%, measured by the official index (IPCA).

In terms of policy directions, these results can be used to support macroeconomic policies, since when there is an exogenous shock the government could stimulate the intersectoral relations in the country through macroeconomic measures, such as appreciate (depreciate) the exchange rate and/or increase (reduce) the interest rate.

Like any model, the main limitation of the present method is its reductionist characteristics. During construction, information is lost; however, this loss was minimized using window-to-window temporal analysis. In addition, topological analysis of the network is affected by the small number of sectors (vertices) considered and, consequently, the emergence of some network properties (e.g., degree distribution) may remain unnoticed.

Even with these limitations, the use of dynamic IO networks properly captures the possible effects of economic shocks on Brazilian intersectoral relations. Given the relevance of the results obtained, we suggest intensifying research focused on IO and network analyses. In this sense, we recommend that future studies apply the methodology developed in this work to relevant economic and environmental issues, for example, trade relations between emerging countries, greenhouse gas emissions (GHG), or water use. For instance, what are the main communities or sectoral clusters in terms of GHG global emissions? And what is the degree of relationship between them? To do so, it is also possible to use others available IO databases, such as OECD-ICIO, EORA and EXIOBASE.

Furthermore, we can also correlate the network metrics with external economics variable (e.g. GDP or labour productivity) in order to make econometric models where the network variables are part of the regression. In this regard, would be possible produce robust results and improve the discussion.

References

Acemoglu D, Carvalho VM, Ozdaglar A, Tahbaz-Salehi A. The network origins of aggregate fluctuations. Econometrica. 2012; 80: 1977-2016.

Atalay E, Hortaçsu A, Roberts J, Syverson C. Network structure of production. PNAS. 2011; 108: 5199-5202.

Bak P, Chen K, Scheinkman J, Woodford M. Aggregate fluctuations for independent sectoral shocks: Self organized criticality in a model of production and inventory dynamics. Ricerche Economiche. 1993; 41: 3-30.

Blöchl F, Theis FJ, Vega-Redondo F, Fisher EO. Vertex centralities in input-output networks reveal the structure of modern economies. Physical Review E. 2011; 83: 046127.

Borghi RAZ. The Brazilian productive structure and policy responses in the face of the international economic crisis: An assessment based on input-output analysis. Structural Change and Economic Dynamics. 2017; 43: 62-75.

Carbonne A, Kaniadakis G, Scarfone AM. Where do we stand on econophysics? Physica A: Statistical Mechanics and its Applications. 2007; 382: 11-14.

Carvalho VM. Aggregate fluctuations and the network structure of intersectoral trade. Economics Working Papers, 1206. Department of Economics and Business, Universitat Pompeu Fabra; 2010.

Carvalho VM, Gabaix X. The great diversification and its undoing. American Economic Review. 2013; 103: 1697-1727.

Carvalho VM, Salehi, AT. Production networks: a primer. Cambridge-INET Working Paper, n.1856, 2018.

Casteigts A, Flocchini P, Quattrociocchi W, Santoro N. Time-varying graphs and dynamic networks. International Journal of Parallel, Emergent and Distributed Systems. 2012; 27: 387-408.

Cepal – Comissão Econômica para a América Latina e o Caribe. Structural change for equality. An integrated view of development. Publicação das Nações Unidas LC/G.2604. Santiago, Chile; 2014.

Cerina F, Zhu Z, Chessa A, Riccaboni M. World input-output network. PLoS ONE. 2015; 10: e0134025.

Dietzenbacher E, Temurshoev U. Input-output impact analysis in current or constant prices: does it matter? Journal of Economic Structures. 2012; 1:4.

Giambiagi F, Villela AA. Economia brasileira contemporânea. Elsevier, 2005.

He X, Yanbo D, Yuying W, Guodan W, Xing L, Yan J. Structure analysis and core community detection of embodied resources networks among regional industries. Physica A. 2017; 479: 137-150.

Hidalgo CA, Hausmann R. The building blocks of economic complexity. PNAS. 2009; 106: 10570-10575.

Holme P, Saramäki J. Temporal networks. Physics Reports. 2012; 519: 97-125.

Hristu-Varsakelis D, Karagianni S, Pempetzoglou M, Sfetsos A. Optimizing production in the greek economy: Exploring the interaction between greenhouse gas emissions and solid waste via input–output analysis. Economic Systems Research. 2012; 24: 55-75.

Jovanovic F, Schinckus C. Econophysics and financial economics: an emerging dialogue. Oxford University Press; 2017.

Kim K, Kratena K, Hewings, GJD. The extended econometric input–output model with heterogeneous household demand system. Economic Systems Research. 2015; 27: 257-285.

Kratena K, Temursho U. Dynamic econometric input-output modeling: New perspectives. In: Jackson R, Schaeffer P, editors. Regional Research Frontiers - Vol. 2: Methodological Advances, Regional Systems Modeling and Open Sciences, Cham, Switzerland: Springer; 2017. pp. 3-21.

Latora V, Marchiori M. Efficient behavior of small-world networks. Physical Review Letters. 2012: 87.

Leontief W. Input-output economics. New York: Oxford University Press; 1966.

Mantegna RN, Stanley HE. An introduction to Econophysics: correlation and complexity in finance. Cambridge University Press; 1999.

Miller RE, Blair PD. Input-output analysis: foundations and extensions. 2nd edition. New York: Cambridge University Press; 2009.

Moreira TM, Ribeiro LCS. Structural changes in the Brazilian economy and the new macroeconomic model: a multisectoral approach. Economia. 2013; 14: 751-780.

Newman M. Networks: an introduction. Oxford University Press, 2010.

Nicosia V, Tang J, Mascolo C, Musolesi M, Russo G, Latora V. Graph Metrics for Temporal Networks. In: Holme P, Saramäki J, editors. Temporal Networks. 1ed. New York: Springer-Verlag Berlin Heidelberg; 2013. pp. 15-40.

Ohnishi T, Takayasu H, Takayasu M. Network motifs in inter-firm network. Journal of Economic Interactions and Coordination. 2010; 5: 171-180.

Pereira EJAL, Silva MF, Pereira HBB. Econophysics: Past and present. Physica A: Statistical Mechanics and its Applications. 2017; 473: 251-261.

Prado EFS. Estrutura tecnológica e desenvolvimento regional. São Paulo: IPE/USP; 1981.

Ribeiro LCS, Domingues EP, Perobelli FS, Hewings GJD. Structuring investment and regional inequalities in the Brazilian Northeast. Regional Studies. 2017; 52(5): 727-739.

Río-Chanona RM, Grujić J, Jensen HJ. Trends of the World Input and Output Network of global trade. PLoS ONE. 2017; 12: e0170817.

Rosário RS, Cardoso PT, Muñoz MA., Montoya P, Miranda JGV. Motif-Synchronization: A new method for analysis of dynamic brain networks with EEG. Physica A. 2015; 439: 7-19.

San Cristóbal JR. A goal programming model for environmental policy analysis: Application to Spain. Energy Policy. 2012; 43: 303-307.

Santos CCR, Cunha MV, Pereira HBB. The complex network of coastal shipping in Brazil. In: Ducruet C, editor. Advances in shipping data analysis and modeling: Tracking and mapping maritime flows in the age of big data. 1ed. New York: Routledge Taylor & Francis Group; 2018. pp. 91-105.

Schinckus C. Introduction to econophysics: Towards a new step in the evolution of physical sciences. Contemporary Physics. 2013; 54: 17-32.

Schweitzer F, Fagiolo G, Sornette D, Vega-Redondo F, Vespignani A, White DR. Economic networks: The new challenges. Science. 2009; 325: 422-425.

Sessa, CB., Simonato, TC, Domingues, EP. O ciclo das commodities e crescimento regional desigual no Brasil: uma aplicação de equilíbrio geral computável (EGC)(No. 551). Cedeplar, Universidade Federal de Minas Gerais, 2017.

Silveira-Neto RM, Azzoni CR. Non-spatial government policies and regional income inequality in Brazil. Regional Studies. 2011; 45: 453-461.

Silveira-Neto RM, Azzoni CR. Social policy as regional policy: Market and nonmarket factors determining regional inequality. Journal of Regional Science. 2012; 52: 433-450.

Solow R. On the structure of linear models. Econometrica. 1952; 20: 29-46.

Souza KB, Ribeiro LCS, Perobelli FS. Reducing Brazilian greenhouse gas emissions: scenario simulations of targets and policies. Economic Systems Research. 2016; 28: 482-496.

Timmer MP, Dietzenbacher E, Los B, Stehrer R, De-Vries GJ. An illustrated user guide to the world input–output database: the case of global automotive production. Review of International Economics. 2015; 23: 575-605.

Tsekeris T. Global value chains: Building blocks and network dynamics. Physica A: Statistical Mechanics and its Applications. 2017 Dec 15;488:187-204.

Tsekeris T. Network analysis of inter-sectoral relationships and key sectors in the Greek economy. Journal of Economic Interaction and Coordination. 2017; 12: 413-435.

Watts DJ, Strogatz SH. Collective dynamics of 'small-world'networks. Nature. 1998; 393 (6684): 440-442.

Xiao H, Sun T, Meng B, Cheng L. Complex network analysis for characterizing global value chains in equipment manufacturing. PLoS ONE. 2017. doi:10.1371/journal. pone.0169549.

Xing L, Dong X, Guan J. Global industrial impact coefficient based on random walk process and inter-country input-output table. Physica A. 2017; 471: 576-591.

Xu M, Allenby BR, Crittenden JC. Interconnectedness and resilience of the U.S. Economy. Advances in Complex Systems. 2011; 14: 649-672.

Figures

Fig 1. General framework of the proposed method for building and analyzing a time-varying weighted network

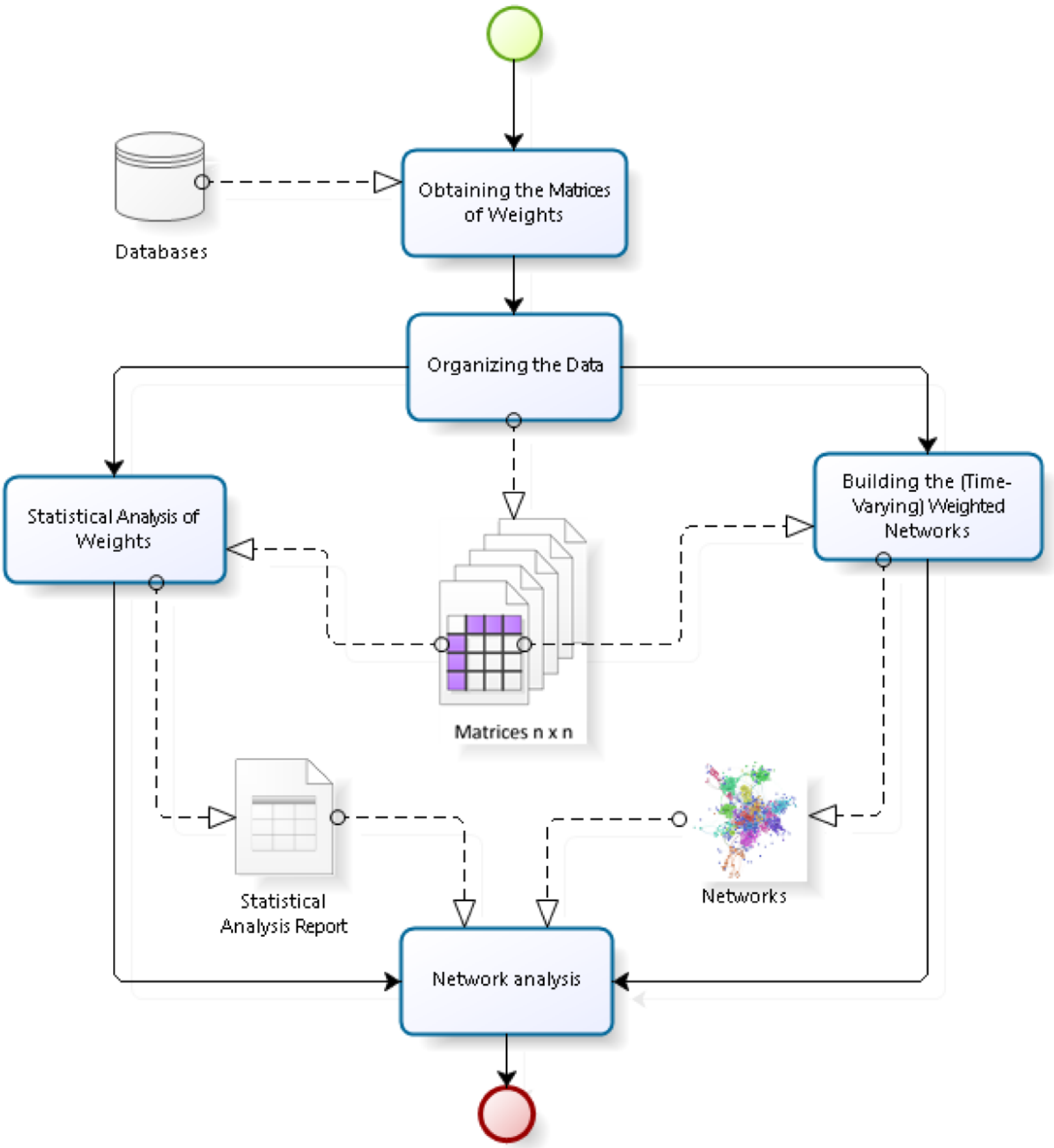

Fig 2. Histogram of all records of the Brazilian IO matrices from 1995 to 2011. The numbers represent the Leontief's inverse matrix coefficients.

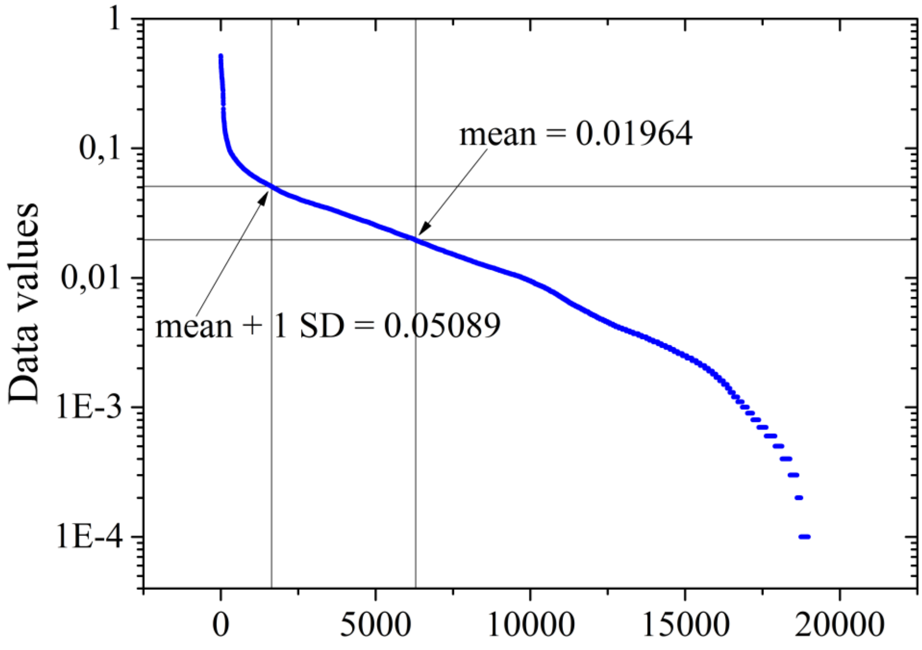

Fig 3. Boxplot of each records of the Brazilian IO matrices from 1995 to 2011, where the dash (—) represents maximum and minimum values of the Leontief's inverse matrix coefficients for each year; the cross (×) represents 99% and 1% percentile of the same data; the little square (□) represents the mean value.

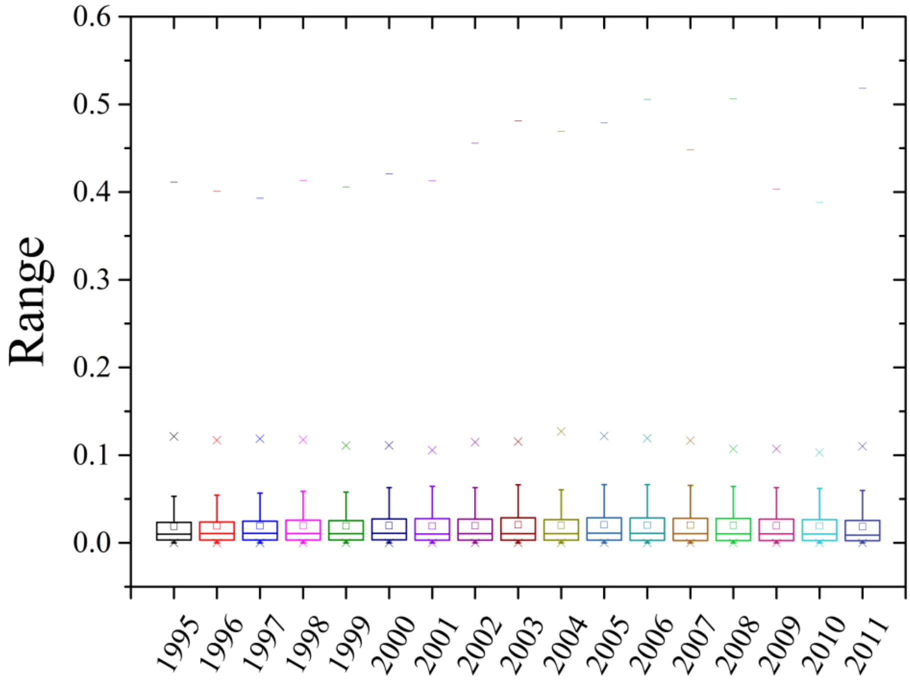

Fig 4. Aggregate static IO networks (a) without filter and (b) with filter $w_{ij} \geq 0.051$. Vertices (i.e. sectors) with higher weighted degree values are painted green, those with lower weighted degree values are painted red, and those with intermediate values are painted with intermediate colors between green and yellow and between yellow and red.

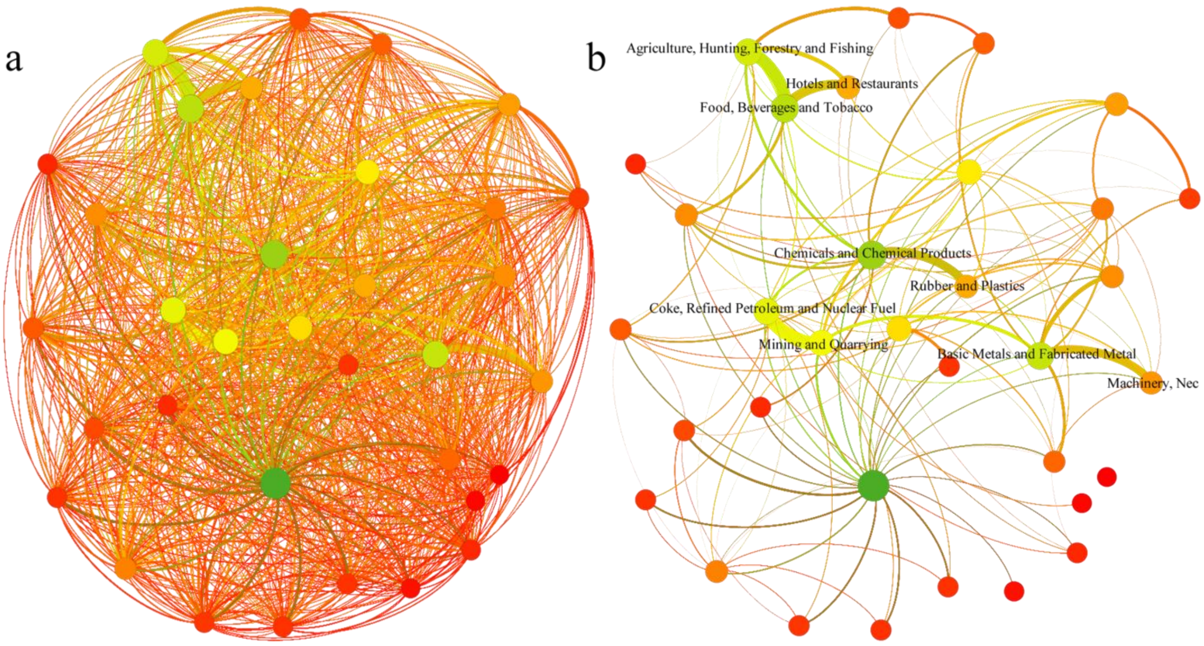

Fig 5. Static IO networks (a) and aggregated static network (b) with $w_{ij} \geq 0.051$. Vertices (i.e. sectors) with higher weighted degree values are painted green, those with lower weighted degree values are painted red, and those with intermediate values are painted with intermediate colors between green and yellow and between yellow and red.

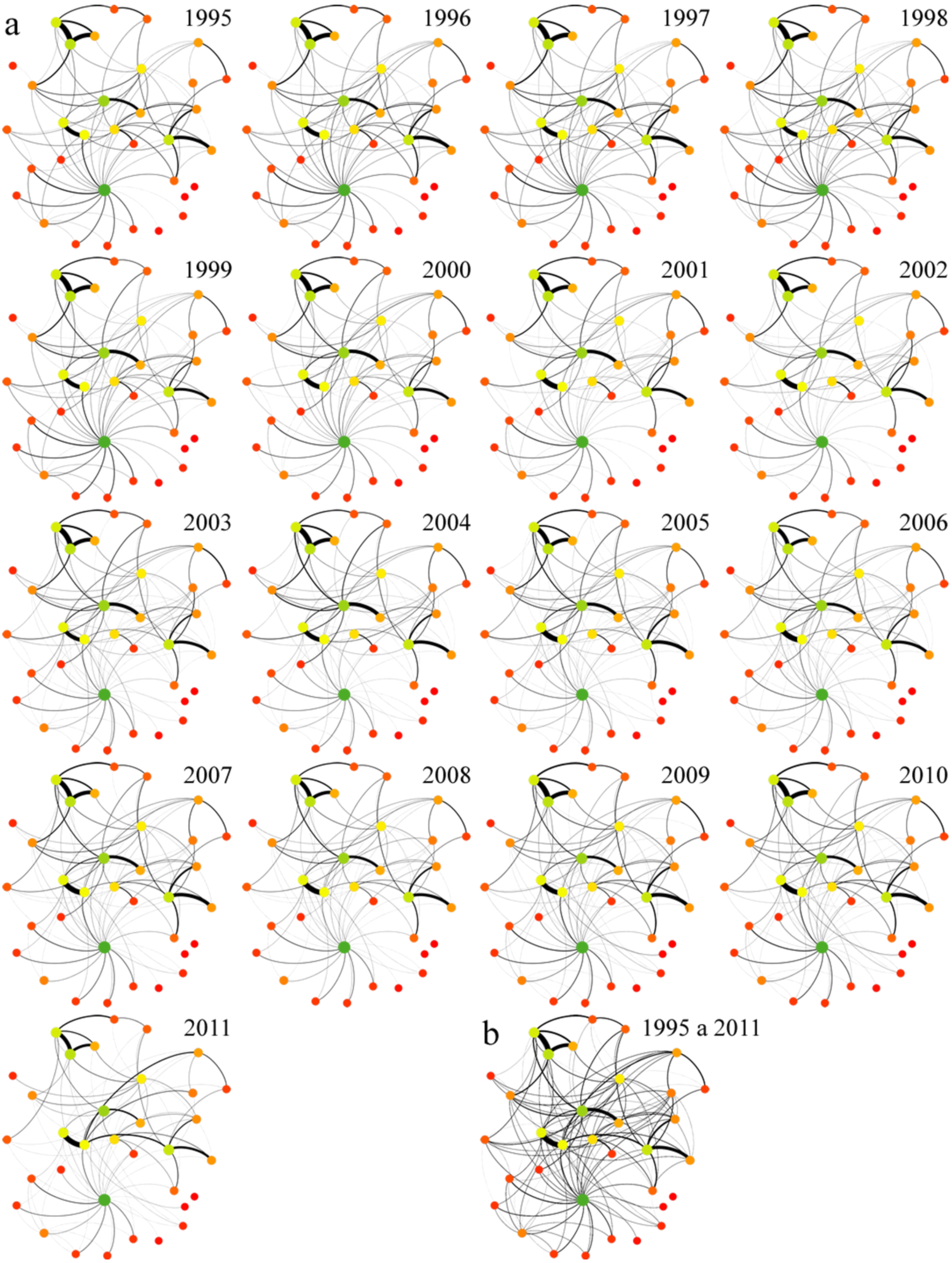

Fig 6. Analysis of IO networks properties of the Brazilian productive structure.

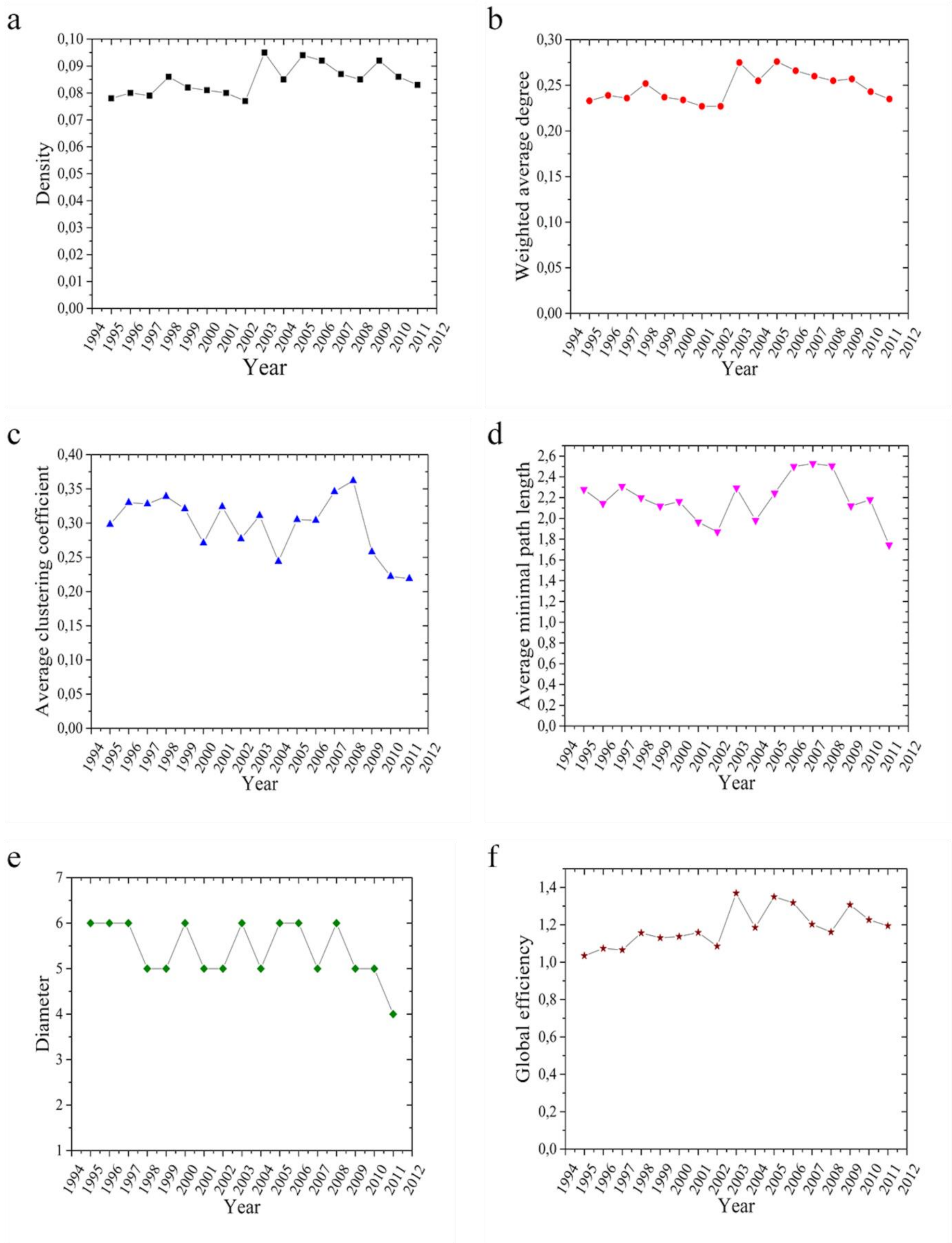

Fig 7. Strongest linkages in the static IO aggregate networks (1995-2011). Vertices (i.e. sectors) with higher weighted degree values are painted green, those with lower weighted degree values are painted red, and those with intermediate values are painted with intermediate colors between green and yellow and between yellow and red.

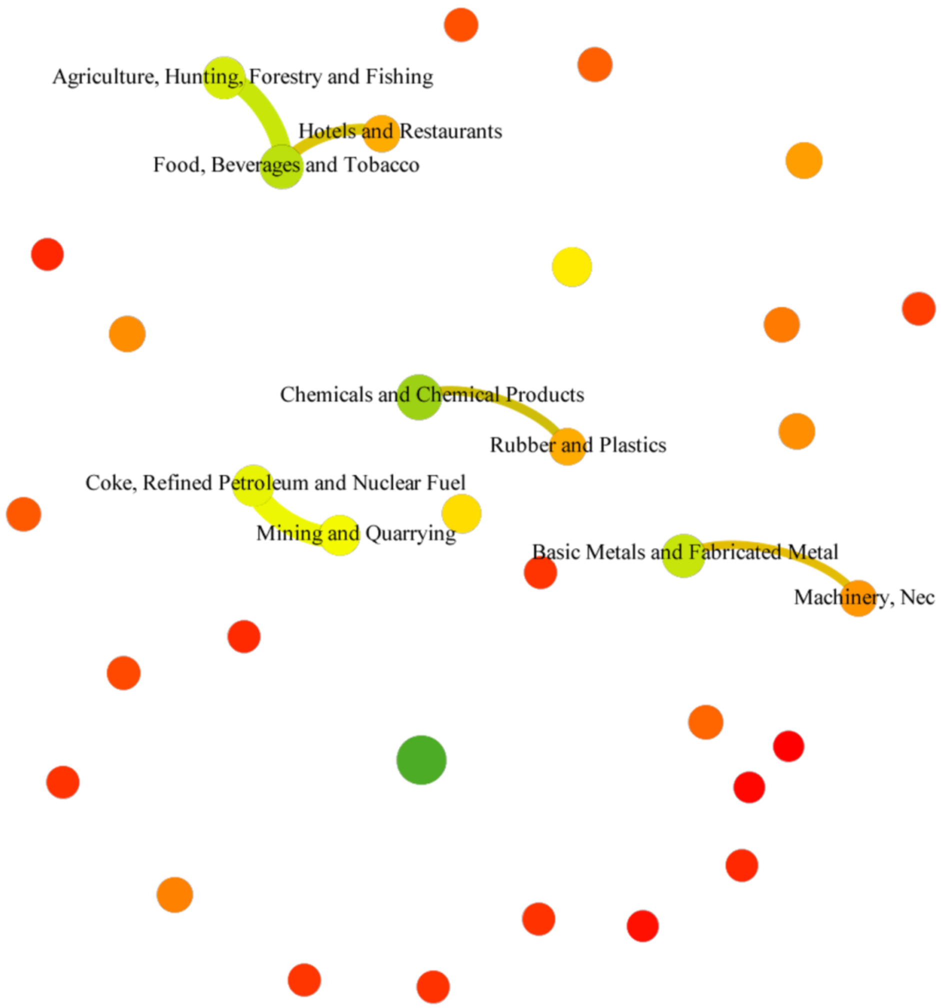

Fig 8. Behavior of the most important sectors with respect to influence over the analysis period (1995-2011) as represented by the average weighted degree.