Modeling Economic Networks with Firm-to-Firm Wire Transfers

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Abstract We study a novel economic network comprised of wire transfers (electronic payment transactions) among the universe of firms in Brazil (6.2 million firms). We construct a directed and weighted network in which vertices represent cities and edges connote pairwise economic dependence between cities. Each city (vertex) represents the collection of all firms within that city. Edge weights are modeled by the total amount of wire transfers that arise due to business transactions between firms localized at different cities. The rationale is that the more they transact with each other, the more dependent they become in the economic sense. We find a high degree of economic integration among cities in the trade network, which is consistent with the high degree of specialization found across Brazilian cities. We are able to identify which cities have a dominant role in the entire supply chain process using centrality network measures. We find that the trade network has a disassortative mixing pattern, which is consistent with the power-law shape of the firm size distribution in Brazil. After the Brazilian recession in 2014, we find that the disassortativity becomes even stronger as a result of the death of many small firms and the consequent concentration of economic flows on large firms. Our results suggest that recessions have a large impact on the trade network with meaningful and heterogeneous economic consequences across municipalities.
1 Introduction

Cities welfare is a crucial component to foster the development of economies both at the regional and national levels. Due to the decreasing trade costs, it is notable the growing specialization of municipalities (Brunelle, 2013). While specialization promotes efficiency gains in the form of economies of scale, it also increases economic dependency among different cities. Such dependency creates the need of cities to transact with each other to ensure provision of all needed goods and services that are not produced locally. The economic dependency among all pairs of cities gives rise to a complex economic network and becomes relevant to be studied under this scenario of rising specialization. Analyzing the economic flows network formed by these economic transactions can uncover many interesting aspects of cities, including their relative importance and substitutability in the national supply chain.

Economic transactions among different cities are mostly performed (in volume) by firms. In this paper, we construct an economic flows network in which connections represent business transactions between firms from different cities. To do so, we use a novel dataset of wire electronic transfers—i.e., payments for specific goods or services from another counterparty—among any two active firms in Brazil from 2002 to 2017. We then aggregate firms within the same municipality to construct a municipality-level network of economic flows. Therein, connections represent the sum of all business payments from two cities that arise due to firm-to-firm payments. With this network, we are able to apply complex network theory to extract topological features and give economic meaning to the most widely used indicators in the related literature.

Brazil has several interesting characteristics that are worth investigating from the viewpoint of economic flows networks. First, it is an important emerging economy that is divided into five vast regions (Northeast, North, Midwest, Southeast, and South) with a total of 5,570 municipalities. Second, due to its continental dimensions and spatial particularities, regions are subject to different climate and geographical conditions, generating the need of trading between different regions. Therefore, we expect that the number of economic transactions between firms residing in different and distant cities to be relevant. Such high number of municipalities and the growing specialization of different cities provide an ideal setup for a complex network analysis that we tackle in this paper. Third, Brazil faced a deep recession from 2014 to 2016 that had strong reflections on firm performance and probability of survival. Many small firms suffered from such recession and went bankrupt. Since our

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1 The more city $i$ transacts with city $j$ (by means of firms residing in each of these cities), the higher the dependency of $i$ on $j$ is. This economic dependency can arise when, for instance, an agricultural firm sells its primary goods to an industrial firm located in another city or even when it sells to an individual outside the city.
dataset goes from 2002 to 2017, we are able to understand how the recession had its tool on the structure of the economic flows network in Brazil.

Most of the works in the empirical literature that employs economic flows networks rely on very aggregate data, such as at the country level. When we are dealing with networks, aggregation can hide important structural aspects of the network and compromise the results and conclusions. For instance, in the case that there are many cycles in the network, the more one aggregates the network by joining vertices one into another, the fewer the number of cycles we get in the resulting network. Therefore, most of the network measures that use interconnection patterns (such as centrality indicators, network cyclicity, average geodesic path, and many others)—and therefore are sensitive to the existence of cycles—become severely compromised, normally having their levels underestimated.

Our data goes from 2003 to 2017, enabling us to understand whether the structure of the Brazilian trade network has changed over time, particularly after the global financial crisis in 2008. We find that the network has a perceptive disassortative mixing, which is consistent with the fact that the firm size distribution in Brazil has a power-law structure (few large firms and many small firms). Interestingly, we find that the network assortativity remains roughly stable from 2003 to 2014, after which it drops. This may be related to the fact that Brazil suffered a deep recession after 2014 and is being at recovery ever since. In these stressed scenario, the number of firms decreased because many firms failed, mostly likely the small ones. In this way, the network became even more disassortative, with large firms concentrating more economic transactions and hence becoming more central.

We find a large degree of economic integration among cities, which we measure using the dependence on external suppliers and customers. This high coupling corroborates the high degree of specialization of cities either in agricultural, industry, or services activities. This evidence favors David Ricardo theory, in which cities should specialize in what they enjoy comparative advantage.

By performing a network centrality analysis, we find that the São Paulo is the most central municipality in Brazil, which is consistent with its largest GDP share in Brazil. Rio de Janeiro follows. Interestingly, the centrality dynamics of São Paulo and Rio de Janeiro are strongly correlated, which reflects their strong economic relationship. While at the regional level average centralities remain roughly the same, if we dive into a state-level analysis, we find some interesting facts. For instance, in the South, Curitiba has been gaining more importance at the cost a fall in centrality of Porto Alegre. In the North region, Belem importance deeply falls after 2008 and Manaus gains the first position in that region. In the Northeast, while Recife and Salvador place at first and second in turns, we see a large increase in importance of Fortaleza, particularly after 2008.

\footnote{For instance, see Serrano and Boguñá (2003); Fagiolo et al. (2008); Fan et al. (2014); Shen et al. (2015) for empirical research on the global economic network. A notable exception is Hussain et al. (2019), who study a network of cities at the global level.}
Our approach is completely novel as this type of dataset is quite difficult to obtain and only countries in which financial authorities track these data can implement such analysis. We contribute to the literature on network analysis by constructing different indexes for each municipality in Brazil using the particularities of the economic network composed of wire transfers among cities.

2 Related Works

Our work closely relates to the literature on economic flows networks. Broadly speaking, we can divide such literature into theoretical- and empirical-oriented work. While theoretical works attempt to explain the nature of connections—i.e., the underlying reasons that promote the existence or absence of links between any two economic agents (such as firms, households, cities, and countries)—empirical works seek to understand the role of the network structure that arise from every connection among economic agents. Our work falls in the second category.

There has been much effort in understanding economic flows networks in the empirical literature. For instance, there is a large body of research studying the world trade economic flows network. In this line of research, Serrano and Boguñá (2003) investigate the topological characteristics of the world trade web modeled as a binary and undirected graph. The work in (Fagiolo et al., 2008) instead uses a weighted network and analyzes the temporal topological properties of world trade economic flows networks. In turn, Fan et al., (2014) explores the countries’ roles in the world trade network using traditional measures borrowed from the complex networks literature while the work in (Shen et al., 2015) uses an approach of flow distances. Our work contributes to this literature by providing a complex network analysis on a more disaggregate data (city level), rather than on very very aggregate data, such as the above-referenced works (country level). The use of more granular data permits us to better reflect the real nature of economic networks.

Our work also connects to the large body of literature discussing networks and financial networks: time-varying causal networks (Song et al., 2016), spillovers in volatility for energy firms networks (Restrepo et al., 2018), effect of networks on innovation (Chuluun et al., 2017), political connections, centrality and firm innovation (Tsai et al., 2019), discussion of the strategic benefit of a firms centrality in its competitive advantage (Larraeta et al., 2019), bank-firm multiplex networks (Li et al., 2019), risk contagion (Wang et al., 2019), systemic risk measures (Guerra et al., 2016), insolvency and contagion (Souza et al., 2015), directed clustering coefficients (Tabak et al., 2014), dynamic spanning trees (Sensoy and Tabak, 2014), classification of emerging markets (Sensoy et al., 2017), feedback centrality of default probabilities (de Souza et al., 2015),

3 For instance, Helpman et al. (2008) develop a model of heterogeneous firms to predict the existence or not of connections between different countries. They find that connections and their trade volume (link weight) yield a generalized gravity equation.
topological properties of stock market networks (Tabak et al., 2010), bank systems supervision (Papadimitriou et al., 2013), calculating systemic risk using feedback between real and financial sectors (Silva et al., 2018) and (Silva et al., 2017a), role of financial institutions (Silva et al., 2016b) and (Ca-jueiro and Tabak, 2008), financial networks and efficiency (Silva et al., 2016a), estimating vulnerability and impact diffusion (Silva et al., 2017b), vulnerability of global financial networks (Silva et al., 2016c), vulnerability cycles (Silva et al., 2017c), and investigation of the network structure and dynamics of regional incubation (Li and Tang, 2019). Our work innovates by documenting structural aspects of a city-level economic networks of an important emerging country (Brazil). Such type of data is difficult to obtain due to its secrecy.

3 Data Description

We use transaction-level data from the SPB, which encompasses the Sistema de Transferência de Reservas (STR) and the Sistema de Transferência de Fundos (CIP-Sitraf), to construct our firm-to-firm network. The BCB maintains both STR and CIP-Sitraf, which are real-time gross settlement payment systems that record electronic interbank transactions in Brazil.

The payment transfers data comprises 6.2 million firms and has about 410 million transactions with a total commercial trading value of R$ 48 trillion among firms between January 2003 and December 2014. To get a sense of the transacted volume, this corresponds to more than 20 times the annual nominal GDP of Brazil in 2014. Our payment data contains about 9 million firm local branches that transacted at least once.

In our analysis, we aggregate payments of all firms residing in the same city, i.e., we go from the more granular firm-time level to the less granular city-time level. The rationale is to understand the network structure of economic inflows and outflows among cities, which can reveal important insights of the economic role and function among cities. Due to this comprehensive dataset, we can map the entire network of economic dependencies among Brazilian cities over time. To avoid considering taxes and public fines, we exclude payments involving wire transfers from firms to the public administration institutions.

We classify cities as suppliers or customers by following the direction of money transfers. Suppliers are receivers of money and therefore reside in the creditor side of the monetary transaction. Customer cities are the payers of the money and are on the debtor side of the transaction. This identification permits us to navigate through the entire supply chain in Brazil. For instance, by following the chains of the supplier to the customer, we navigate downstream in the supply chain.

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4 CIP-Sitraf clears most of the transfers in Brazil. STR is used to clear high-valued transactions. In this way, CIP-Sitraf has the largest quantity of payments, mainly of low values. STR, on the other hand, has fewer transactions but concentrate the most representative volume of monetary transfers.
4 Network measurements

Complex networks have been used in a wide area of applications. This include areas as diverse as Biology (Kugler et al., 2011; Konini and van Rensburg, 2017), Natural Language Processing (Akinushkin et al., 2017; Amancio et al., 2015; Amancio, 2015), Data Science (Pham et al., 2015), Scientometrics (Wang et al., 2017; Araújo et al., 2014; Correa Jr et al., 2017) and Time Series Analysis (Gao et al., 2015b, 2013a, 2015a, 2013b). A network comprises nodes, which are linked via edges. Several measurements have been devoted along the last years to study the network structure. Below we summarize some of the most important measures used for this purpose. These measurements are used here to study the main properties of the network modeling intercity economic flows.

1. **Density**: the density of a network measures how connected is the network. It is defined as the ration between the number of edges and the total number of nodes in a complete network with the same number of nodes. In other words, if $E$ is the number of edges and $N$ is the number of nodes, the density is defined as $d = \frac{E}{N(N - 1)}$.

2. **Degree**: the degree of a node is related to the total number of links linked to that node.

3. **Assortativity**: this measurement quantifies whether edges link nodes with similar characteristics. In this case, a network is assortative if highly connected nodes tend to connect with other highly connected nodes. Conversely, a network is disassortative if highly connected nodes are linked with low-degree nodes. This measurement can be quantified by measuring the degree correlation of linked nodes.

4. **Diameter**: the diameter of a network is related to the concept of shortest path (Newman, 2003). A shortest path is a path in a network linking two nodes with minimum length. The diameter of the network is maximum shortest path length linking the nodes in the network.

5. **PageRank**: the PageRank algorithm is a method to measure the importance of nodes in the network. Unlike other measurements based on strictly local features (such as degree) or quasi-local features (such as hierarchical measurements (Amancio et al., 2012)), the PageRank uses global information to measure the centrality of a node. More specifically, the importance of a node is proportional to the importance of nodes linked to it. Mathematically, the PageRank $\pi(v_i)$ of node $v_i$ is computed as

\[
\pi(v_i) = \frac{1 - \alpha}{N} + \alpha \sum_{v_j \in V(v_i)} \frac{\pi(v_j)}{K(v_j)},
\]

where $\alpha$ is a constant to account for the probability that a random walker visit a randomly picked node in the whole network, $V(v_i)$ is the set of nodes connected to $v_i$ (in-going links to $v_i$) and $K(v_j)$ is the set of outgoing links from $v_j$. 
While there are many other complex network analysis, here we decided to focus on the most common measurements to characterize the main topological features of the network. A detailed description of the above measurements and more applications can be found elsewhere (Newman 2018).

5 Network topological analysis of the Brazilian intercity economic flows

In this section, we analyze the structural features of the Brazilian network of intercity economic flows using complex network theory. We follow Silva and Zhao (2016)'s classification of network measures.

We start with global network measures. Figure 1 portrays the network assortativity. We observe that the Brazilian network of intercity economic flows presents a disassortative mixing, with an average assortativity of $-0.25$ from 2002 to 2017. In this setting, small cities tend to connect to bigger cities, which act as hubs to the entire supply chain of Brazil. This network structure also has small network diameter, suggesting the existence of the small-world phenomenon in the network structure. That is, regardless of the geographical distances, cities tend to reside near each other in the economic sense (connections in the network).

![Fig. 1 Assortativity obtained from the Brazilian intercity trade network. The data was obtained in the period between 2003 and 2017.](image)

Looking at Figure 1 we observe three regions with different dynamics. From 2002 to 2005, we observe a tendency of a more disassortative network, suggesting that city hubs tend to concentrate more connections and hence become more important to the economic flows among cities in Brazil. From 2006
to 2012, we have the opposite feature: the network tends to become more assortative, meaning that connections become more dispersed throughout other cities apart from the hubs. This reduces the relative network importance of the hubs and fosters the existence of more local economic dependency rather than national dependencies warranted by the hubs, which link cities far apart from each other. Finally, from 2013 to 2017, we see a strong decrease of the network assortativity, raising the importance of city hubs to the entire national supply chain. City hubs are the most central cities in the network, which we identify in this sector later on.

Figure 2 exhibits the network density—an another global network measure—of the Brazilian network of intercity economic flows. We observe that the density ranges from roughly 0.0025 to 0.0325. We can interpret these numbers as probabilities: if we randomly take two cities in Brazil, there is a probability that they transact with each other of 0.25% in 2002 and 3.25% in 2017, conditioned on the observable wire transfers. Following the rule-of-thumb in the complex network literature, this network is considered as very sparse, which corroborates the existence of small city centers that link regional cities far apart. These regional cities have small degree (number of other city counterparts) and strength (intensity of transfers to other counterparts) network measure, while those centers have high degree and strength.

![Figure 2](image.png)

**Fig. 2** Density obtained from the Brazilian intercity trade network. The data was obtained in the period between 2003 and 2017.

Table 1 reports the ranking of the top 30 most central cities in the Brazilian network of intercity economic flows in 2003 and 2014. The network centrality is a mixed network measure because it uses not only topological network information in the direct neighborhood but also in indirect neighborhoods.
We take Google PageRank as our baseline network measure. We observe the identified top 10 most central cities remain the same regardless of the network centrality and the year analyzed. We see more fluctuations of the other cities in the rank.

City capitals are the ones that tend to connect cities far apart and therefore are the most probable candidates of being hubs of the supply chain in Brazil. Figures 3–4 show the evolution of the network centrality for the capitals of the Southeast, South, North, Northeast, and Midwest regions, respectively. São Paulo is by far the most central city in Brazil, followed by Rio de Janeiro, both located in the Southeast region. It is interesting to observe the dynamics of Brazilian capitals over time. While São Paulo and Rio de Janeiro are the most important hubs, their relative importance to the entire network remains stable over time.

**Fig. 3** Evolution of network centrality for capitals of the Southeast Region. We considered data retrieved between 2003 and 2014.

The relative importance of some capitals change over time. For instance, in the South region, the relative importance Curitiba quickly increases after 2011, while that of Porto Alegre decreases in the same period. In the North, Belém remained as the most important regional center until 2008, after which Manaus took the top 1 place in the region. All the other capitals in the North have very small importance, suggesting that the link of the North region to the remainder of the country goes through Manaus and Belém. In the Northeast region, we observe a large heterogeneity. While we observe a steady and large importance
Table 1: Ranking of 30 Municipalities with the highest centrality. We considered the years 2003 (see left panel) and 2014 (see right panel).

| 2003 | Ranking | Centrality | Municipality | State | Region |
|------|---------|------------|--------------|-------|--------|
| 1    | 100%    | So Paulo   | So Paulo     | Southeast |
| 2    | 73%     | Rio de Janeiro | Rio de Janeiro | Southeast |
| 3    | 15%     | Barueri    | So Paulo     | Southeast |
| 4    | 14%     | Brasilia   | Distrito Federal | Midwest |
| 5    | 12%     | Osasco     | So Paulo     | Southeast |
| 6    | 8%      | Porto Alegre | Rio Grande do Sul | South |
| 7    | 7%      | Curitiba   | Paran          | South |
| 8    | 7%      | Campinas   | So Paulo     | Southeast |
| 9    | 6%      | Osasco     | So Paulo     | Southeast |
| 10   | 6%      | Belo Horizonte | Minas Gerais | Southeast |
| 11   | 5%      | So Bernardo do Campo | So Paulo | Southeast |
| 12   | 4%      | So Caetano do Sul | So Paulo | Southeast |
| 13   | 4%      | Jaguarina  | So Paulo     | Southeast |
| 14   | 4%      | Salvador   | Bahia          | Northeast |
| 15   | 4%      | Belm       | Par             | North |
| 16   | 4%      | So Jos dos Campos | So Paulo | Southeast |
| 17   | 4%      | Betim      | Minas Gerais  | Southeast |
| 18   | 4%      | Guarulhos  | So Paulo     | Southeast |
| 19   | 4%      | Fortaleza  | Ceara          | Northeast |
| 20   | 4%      | Camaari    | Bahia          | Northeast |
| 21   | 4%      | Florianopolis | Santa Catarina | South |
| 22   | 4%      | Santo Andre | So Paulo     | Southeast |
| 23   | 4%      | So Lus Maranhao | Maranhao | Northeast |
| 24   | 4%      | Betim      | Minas Gerais  | Southeast |
| 25   | 4%      | Guarulhos  | So Paulo     | Southeast |
| 26   | 4%      | Duque de Caxias | Rio de Janeiro | Southeast |
| 27   | 2%      | So Jos dos Campos | So Paulo | Southeast |
| 28   | 2%      | Uberlandia | Minas Gerais | Southeast |
| 29   | 2%      | Joao Pessoa | Paraiba       | Northeast |
| 30   | 2%      | Contagem   | Minas Gerais  | Southeast |

| 2014 | Ranking | Centrality | Municipality | State | Region |
|------|---------|------------|--------------|-------|--------|
| 1    | 100%    | So Paulo   | So Paulo     | Southeast |
| 2    | 79%     | Rio de Janeiro | Rio de Janeiro | Southeast |
| 3    | 72%     | Brasilia   | Distrito Federal | Midwest |
| 4    | 51%     | Osasco     | So Paulo     | Southeast |
| 5    | 47%     | Porto Alegre | Rio Grande do Sul | South |
| 6    | 46%     | Curitiba   | Paran          | South |
| 7    | 42%     | Campinas   | So Paulo     | Southeast |
| 8    | 39%     | Osasco     | So Paulo     | Southeast |
| 9    | 38%     | Belo Horizonte | Minas Gerais | Southeast |
| 10   | 33%     | So Bernardo do Campo | So Paulo | Southeast |
| 11   | 32%     | So Caetano do Sul | So Paulo | Southeast |
| 12   | 31%     | Jaguarina  | So Paulo     | Southeast |
| 13   | 31%     | Salvador   | Bahia          | Northeast |
| 14   | 30%     | Belm       | Par             | North |
| 15   | 29%     | So Jos dos Campos | So Paulo | Southeast |
| 16   | 29%     | Betim      | Minas Gerais  | Southeast |
| 17   | 28%     | Guarulhos  | So Paulo     | Southeast |
| 18   | 28%     | Fortaleza  | Ceara          | Northeast |
| 19   | 28%     | Camaari    | Bahia          | Northeast |
| 20   | 27%     | Florianopolis | Santa Catarina | South |
| 21   | 27%     | Santo Andre | So Paulo     | Southeast |
| 22   | 26%     | So Lus Maranhao | Maranhao | Northeast |
| 23   | 26%     | Betim      | Minas Gerais  | Southeast |
| 24   | 26%     | Guarulhos  | So Paulo     | Southeast |
| 25   | 25%     | Duque de Caxias | Rio de Janeiro | Southeast |
| 26   | 24%     | So Jos dos Campos | So Paulo | Southeast |
| 27   | 24%     | Uberlandia | Minas Gerais | Southeast |
| 28   | 23%     | Joao Pessoa | Paraiba       | Northeast |
| 29   | 23%     | Contagem   | Minas Gerais  | Southeast |

Centrality values are normalized, therefore we interpret them as relative values to the most central city (So Paulo in both years).
for Recife and Salvador, the importance of Fortaleza quickly increases after 2007. The role of So Luís and João Pessoa in the network decreases before 2008, and remains rather stable after then. In the Midwest, we observe a quick increase of the importance of Brasília throughout the entire analyzed period.

Table 2 shows the top 30 cities with largest dependence on external customers and suppliers in 2014, respectively. These measures are strictly local. That is, their economic relies on customers buying or suppliers selling products/services in other cities rather than within the same city. A large external dependency corroborates the Ricardian theory of comparative advantage in which cities should specialize in the production of those goods and services in which they enjoy comparative advantage. In this case, we would observe a large economic integration among cities. Overall, we observe a high external dependence, allowing us to conclude for the existence of a strong economic integration across Brazilian cities.

6 Conclusion

This paper uses a novel dataset composed of wire transfers to study how cities interconnect in a large and important emerging country. Brazil has over 5,500 municipalities, which together potentially create a very heterogeneous topological structure among different cities. The application of complex network theory in this type of economic network enables us to understand how supply
| Ranking | DOEC (2014) | Municipality | State | Region |
|---------|-------------|--------------|-------|--------|
| 1       | 100.00%     | Cachoeira Grande | Maranhão | Northeast |
| 2       | 100.00%     | So Gonalo do Gurguia | Piau | Northeast |
| 3       | 100.00%     | Jardim de Angicos | Rio Grande do Norte | Northeast |
| 4       | 100.00%     | Vila Flor | Rio Grande do Norte | Northeast |
| 5       | 100.00%     | Curral Velho | Pará | Northeast |
| 6       | 100.00%     | So José de Princesa | Pará | Northeast |
| 7       | 100.00%     | Serra Redonda | Pará | Northeast |
| 8       | 99.71%      | Tupirama | Tocantins | North |
| 9       | 99.62%      | Serra do Navio | Amapá | North |
| 10      | 99.55%      | Pau D'Arco do Piauí | Piauí | Northeast |
| 11      | 99.33%      | Peixe | Tocantins | North |
| 12      | 99.28%      | Parari | Pará | Northeast |
| 13      | 99.00%      | Piauí | Minas Gerais | Southeast |
| 14      | 98.65%      | Passagem Franca | Piauí | Northeast |
| 15      | 98.35%      | Treviso | Santa Catarina | South |
| 16      | 98.18%      | Rafard | São Paulo | Southeast |
| 17      | 98.09%      | Guara Nova | Rio Grande do Norte | Northeast |
| 18      | 98.02%      | Salmouro | São Paulo | Southeast |
| 19      | 97.97%      | Salgado de São Félix | Pará | Northeast |
| 20      | 97.65%      | Major Gercino | Santa Catarina | South |
| 21      | 97.61%      | Quat | São Paulo | Southeast |
| 22      | 97.51%      | Viosa | Rio Grande do Norte | Northeast |
| 23      | 97.43%      | Mutupe | Bahia | Northeast |
| 24      | 97.41%      | Jenipapo de Minas | Minas Gerais | Southeast |
| 25      | 97.25%      | So Francisco do Pará | Pará | North |
| 26      | 97.15%      | Bom Jardim da Serra | Santa Catarina | South |
| 27      | 97.14%      | So Miguel da Baixa Grande | Piauí | Northeast |
| 28      | 97.10%      | Areia de Baranas | Pará | Northeast |

Table 2: Ranking of the 30 Municipalities with the Largest Dependence on External Customers and Suppliers (DOEC, DOES) in 2014.
chains interconnect across different cities, how central (important) are different cities, and how its structure changes over time.

We observe that the trade network has a pronounced disassortative mixing pattern, which relates to the power-law shape of firm distributions in Brazil (many small firms and few large firms). We also find that the assortativity drops after the Brazilian recession in 2014, which may be related to the fact that small firms failed and large firms concentrated even more economic flows.

We find a large degree of economic integration among cities, which we measure using the dependence on external suppliers and customers. This high coupling corroborates the high degree of specialization of cities either in agricultural, industry, or services activities. This evidence favors David Ricardo theory, in which cities should specialize in what they enjoy comparative advantage.

Municipal capitals are those that tend to connect cities that are very separate and, therefore, are the most likely candidates to be centers of the supply chain in Brazil. The relative importance of some cities varies over time. We predict that the ten main cities identified remain the same regardless of the centrality of the network and the year analyzed. We see more oscillations of the other cities.

Using the network density, we find that the trade network is very sparse, which confirms the existence of small urban centers that link very remote regional cities.

We find a network core consisting of cities in the southeast region (metropolitan areas of Belo Horizonte, Campinas, Rio de Janeiro and Sao Paulo), the southern region (metropolitan areas of Curitiba and Porto Alegre) and the Federal District.

Our results are important for the design of public policies as we can track down the most relevant cities in a connectedness perspective. Which cities perform a function of core in the network and may help speed up economic growth. Further research could explore the network using a variety of networks measures to deepen our understanding of the evolution of these networks.

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