Sectoral Market Power in Global Production: A Theoretical and Observational Study

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Abstract

In a globalized world, the distribution of value-added across firms depends on a number of factors that vary across space. A key factor is related to the different types of competition on the multilayer structure of production, which are characterized by different types of (market) power. In this paper, we first argue that PageRank centrality is able to capture sectoral market power within the complex structure of global production. We then study the empirical properties of this market power measure and demonstrate a power-law relationship between sectoral PageRank centrality and relative sectoral profits. This power-law relationship has (international) political economy implications as it demonstrates the high incentives of sectors to become more central to increase their relative profits.

Keywords: Global Production Networks, Market Power, Centrality Distributions, Power Law

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1. Introduction

Market power captures the ability of market participants to influence the price of a commodity, or any other market outcome linked to the allocation of resources. It is well known that under the assumption of perfectly competitive markets, outcomes are optimal for both producers and consumers (Mas-Colell et al., 1995; Varian, 1992), while deviations from the perfect competition allow certain market participants to use the market mechanism for their own interest. These deviations define special cases of market imperfections and have been the theoretical and empirical focus of alternative approaches. A number of these approaches focus on the role of monopolies, oligopolies and oligopsonies, on the determination of prices, income distribution, resources allocation, etc., linking market power with class conflict and socio-economic outcomes (see for example Baran and Sweezy, 1966; Lavoie, 2014; Shaikh, 2016).

Taking into account different forms of market power is relevant for the analysis of international trade and global production, where firms' (market) power translates into the ability of lead firms to shape governance structures of their respective value-chains, capturing the highest possible amount of value-added. Several analytical frameworks have been proposed, emphasizing different dimensions of (market) power relations along the various levels of production. For example, the Global Commodity Chains (GCC) framework (Gereffi, 1994) focuses on the technological differences in production processes to explain the birth and evolution of global commodity chains, driven by either large and powerful producers (Producer-Driven) or sizeable and dominant buyers (Buyer-Driven). On the other hand, the Global Production Networks (GPN) framework (Henderson et al., 2002) stresses the bidimensionality of power, which is perceived as both a topological characteristic of the position (positionality) each actor holds in the production network, as well as a relational attribute of the exchange relations between network participants. The more recent GPN 2.0 framework (Coe and Yeung, 2015) goes one step further, arguing that power relations and asymmetries are latently embedded into specific configurations of global production networks.

However, in the above-mentioned frameworks, the conceptualization and operationalization of market power become much more complex. Each firm receives inputs from a firm at a lower tier in the production process and provides inputs to firms at a higher tier. This leads to the question of how can – or should – market power be thought and conceptualized when firms operate within global value chains. Depending on the level of analysis, one can investigate the characteristics of a firm, sector, or supply chain with respect to the distribution of value-added in the various levels of analysis. We acknowledge that the specific choice of a level of analysis comes with both advantages and drawbacks. While the focus on a firm-level is able to provide detailed insights regarding the market power dynamics of specific firms, it lacks both the data availability and the generality of the policy implications that come when choosing to focus on a more aggregate level. One way to deal with this issue is by acknowledging that firms are parts of sectors within countries and hence share - to some extent - the sectoral characteristics regarding the distribution of value-added. However, while more data are available on a sectoral level, it is not clear what is the appropriate notion of power able to capture the complexity of global production. Our paper aims to contribute to this direction both theoretically and empirically by focusing on the profitability of national sectors in relation to their (network) position within a global production process. More specifically, we argue that network positionality on a sectoral level defines a form of market power, which we refer to as sectoral positional power.

On a theoretical level, we argue that a proper measure of sectoral positional power should concretely consider the market power dynamics across different production levels. This is due to the fact that the market power of a sector is a function of the relative market power of sectors in both higher and lower tiers of production, also considering the total value added produced in the process. Hence the appropriate measure should have two key characteristics: (i) take into account not only how connected is one sector but also how well connected the other sectors are connected to the former, and (ii) take into account the volume of transactions. These two characteristics correspond to the measure of PageRank centrality, and as such, PageRank centrality is an appropriate measure of sectoral positional power.

On an empirical level, we first observe that the distribution of both sectoral relative profits and PageRank centrality across sectors exhibit heavy tails, whereas goodness-of-fit statistical tests indicate that they follow either a power law or a log-normal distribution. The distribution of the relative profits highlights that a small number of sectors has a relatively high share of profits and similarly that the (PageRank) centrality of most sectors is low, while for some, it is relatively high. Given this observation, we then investigate whether there is an association between the logarithms of the two variables, hence indicating a power-law relationship between the two. We observe a relatively strong correlation and find that a statistically significant relationship exists between the logarithms of the two variables. Furthermore, our regression shows an exponent around 2 for the heavy-tail relationship. Our empirical observations demonstrate the centralisation incentives of sectors and hence of the firms that belong to each of these.

The two levels of analysis of our paper contribute and connect two distinct streams of literature that have not been interacting to any significant extent up to now. Within the broader field of international economics, international political economy and economic geography, our theoretical analysis contributes to the global production literature through highlighting the importance of sectoral level analysis in global production and introducing a measure of market power building on relevant network centrality concepts (Acemoglu et al., 2012; Antràs et al., 2012; Hummels et al., 2001). Furthermore, by showing the heavy-tailed properties of this market power measure, our paper is related to the empirical literature, which focuses on power-law patterns in economic geography (for example, see Gabaix, 2016).

Our paper also contributes to the economics literature, which utilizes tools and insights from complex systems and network theory to study how the network structure of production affects macroeconomic dynamics and also how economic factors affect the production network (for example, see Amador and Cabral, 2017; De Masi and Ricchiuti, 2020; Giammetti et al., 2020; McNerney et al., 2022; among others). Our work extends this stream of work by looking at how the global structure of production has implications on a meso level of analysis.

The structure of the rest of the paper is as follows. Section 2 discusses the contribution of the paper with respect to the different pieces of literature in more detail. Section 3 introduces the key characteristics of sectoral market power and argues that PageRank centrality captures these characteristics well and hence can be a measure of sectoral market power. Section 4 presents relevant empirical observations which show a power-law relationship between PageRank centrality and relative profits. The final section provides a summary discussion and directions for future research.

2. Relevant literatures

Whilst perfect competition is a theoretical case of an ideal market for which very restrictive and unrealistic assumptions have to be made, it is widely used in modern economics textbooks and economic policy institutions both as a benchmark and due to its desirable welfare and efficiency properties (Shepherd and Shepherd, 2003). A number of approaches expand the conceptual space of market power, in order to include, not only economic factors, like prices and costs, but also the political and social environment (Baran and Sweezy, 1966). For example, Kalecki (1938, 1968) and the literature which draws on his work (for example, see Lavoie, 2014 and references therein) argues that the main objective of firms is the maximization of power, defined as the ability of a firm, notwithstanding its size, to "have control over future events, its financial requirements, the quality of its labour force, the prices of the industry, the possibility of takeovers" (Lavoie, 2014: 128–129). In the Kaleckian framework, firms set their prices by applying a stable (monopoly) markup over their average costs, which in turn are determined by market structural factors, such as the market concentration, the labor costs, and the cost of intermediate inputs (Lavoie, 2014; Sawyer, 1985). Given the role of intermediate goods, this approach has been very relevant in the analysis of global production processes and several works within international economics, international political economy, and economic geography, incorporate insights related to this broader notion of power to light on the new patterns of international fragmentation of production and the organization of Global Value Chains (Coe and Yeung, 2015; Gereffi, 2018).

In this paper, we refer to the GCC, GVC and GPN frameworks, as the most characteristic examples of this extant literature, that focuses on outsourcing and offshoring. Starting with the notion of governance structures, defined as the 'authority and *power relationships* that determine how financial, material and human resources are allocated and flow within a chain' (Gereffi, 1994: 97, emphasis added), Gereffi provided the first conceptualisation of inter-firm power relations in a commodity chain. His dichotomy between producer-driven (PD) and buyer-driven (BD) value-chains broke new ground by constructing a framework to analyse global production processes. However, it was critiqued for treating the process as too static, forbidding the co-existence of BD and PD governance structure along the same value chain (Dallas et al., 2019: 669) and leaving little room for analyzing the transformation of governance structures (Gibbon et al., 2008).

As a result, a new framework initiated by Gereffi, Humphrey and Sturgeon (2005) – global value chains – attempted to overcome the limitations of GCCs while simultaneously expanding its analytical scope. As far as power relations were concerned, Gereffi et al. (2005) proposed a fivefold typology of governance structures (Market, Modular, Relative, Captive, Hierarchical) dependent upon three factors: the complexity of transactions, codifiability of information, and supply-base capabilities. In turn, these governance structures corresponded to a continuum of degrees of explicit coordination and *power asymmetry*, spanning from low values characterizing the market governance structure to higher and higher values as the structures move from the market towards a hierarchical governance structure.

Despite the improvements proposed by the new governance typology of Gereffi et al. (2005), many maintained that it remained still too static and homogenized in nature, with geographical, social and institutional specificities unaccounted for (Coe et al., 2008; Dicken et al., 2001; Gibbon et al., 2008; Henderson et al., 2002). This critique led to the development of a new framework, the GPN, which conceptualized the world economy as a network connecting different economic and non-economic actors. In this way, the notion of power reflects both the topological-positional characteristics of network actors (structural dimension) and the qualitative characteristics of the linkages in a production network (relational dimension) (Dicken et al., 2001: 93). Even though this approach aimed to include more actors by doing so, it has not been able to provide a notion of power defined at least as clearly as in the proceeding analytical frameworks.

The next version of the GPN framework, the GPN 2.0, put more emphasis on the analytical role played by network configurations, as the reflection of the actor-specific strategies, with respect to power dynamics, highlighting the importance of actor-specific strategies shaped by the confrontation of network agents against certain competitive dynamics (Coe and Yeung, 2015: 65). Even though GPN 2.0 takes an essential step in linking power with the network configuration of the global production processes, it does not provide either a specific definition of this power or what drives it.

The aforementioned literature sparked a vibrant discussion around the issues of power where each stage identified important limitations in the respective analytical frameworks and thus paved the way for the subsequent theoretical and empirical development (Dallas et al., 2019; Galanis and Kumar, 2020; Kumar, 2020; Mahutga, 2014; Rutherford and Holmes, 2008; Tonts et al., 2012). Notwithstanding the interest in the issues of power relations in global production, the focus has been primarily on firms incorporating a micro-level conceptualization of market power and market structures without adequately considering the fact that firms belong to national sectors. Hence sectoral power is a possibly important factor to take into account. For these approaches, the market power is usually translated into the ability of lead firms to shape and dominate governance structures and thus be able to capture higher proportions of the produced value-added along the various stages of the value chain.

Moreover, the complexity of conceptualizing and operationalizing market power at the global level is higher compared to the macro-based approaches of the heretofore literature. Global production integrates firms that belong to different sectors, geographies, and institutional environments and consequently own different levels of market power with respect to their customers downstream and their suppliers upstream. Ignoring the dimension of the global production structure and how it influences market power poses significant difficulties in our understanding of power relations at the global level. Apart from the significance on a theoretical level, given the availability of sectoral level input-output data, a sectoral analysis is able to allow for empirical investigation of market power.

Our paper contributes to the above literature by introducing sectoral PageRank centrality as a measure of power that is both quantifiable and can capture the complex structures of global production and assess the relationship between sectoral market power and profit distribution which has not yet been explored. In this way, our work links the GVC/GPN literature on power with the extensive literature focusing on the network properties of firms (see Amador and Cabral, 2017; De Masi and Ricchiuti, 2020; Giammetti et al., 2020; McNerney et al., 2022; among others).

Furthermore, our empirical findings are related to a number of works which focus on power-law dynamics. First, extensive literature looks at power laws in global production networks. Investigating the heavy tail characteristics of the distribution of US inter-sectoral transactions, Xu, et al. (2011) conclude that the size and transactions' strength among sectors are not homogenous, rendering some critical sectors important for the resilience of the US economy to crises and shocks. Similarly, Contreras and Fagiolo (2014), applying various diffusion models to the analysis of crisis propagation in EU production networks, find that the structures of European economies are highly asymmetrical, a property that is "important in determining the propagation of shocks". Likewise, Cerina et al. (2015) contend that at the global level, national industries are highly, but asymmetrically connected, based on the observation of the heavy tail distributions of Degree and Strength centralities, implying that micro shocks found in one industry in one country, could translate into worldwide macroeconomic fluctuations. Additionally, power-law distributions have been observed in firms' size (see Axtell, 2001; Bottazzi et al., 2011, 2015; Calvino et al., 2018; among others). Third, power laws have been extensively studied in urban economics (see Gabaix and Ioannides, 2004; Hsu, 2012; Su, 2020).

Finally, our empirical observations contribute to the literature, which focuses on the empirical analysis of global value chains in terms of the depth of spatial production fragmentation and the re-integration of the global economy through international trade. These works assess the scope and length of production fragmentation (Antràs et al., 2012; Antràs and Chor, 2018; Feenstra, 1998; Milberg and Winkler, 2013), explore the structural characteristics of international trade patterns (Fagiolo et al., 2009; Hausmann and Hidalgo, 2011; Serrano and Boguñá, 2003), analyze the shock propagation properties of global production structures (Acemoglu et al., 2012; Gabaix, 2011) and measure the volumes of value-added in exports and imports of trading nations (Hummels et al., 2001; Johnson, 2018; Koopman et al., 2012).

3. Sectoral Market Power in Global Production

We assume a global production network consisting of a large number of firms where each firm (*f*) is characterized by two key variables: the type of task that it performs in the production process, call this task t^i, and the country that it resides, call this c^j, where $i = \{1, 2, ..., N\}$ and $j = \{1,2, ..., M\}$ capture N different production processes in M countries respectively. If for example t^1 is construction and c^{17} is India, then any construction firm in India can be denoted by $f(t^1, c^{17})$.

Each firm can have its own characteristics which would differentiate it compared to other firms with the same t^i and c^j, hence we can denote by $f^k(t^1, c^{17})$ a specific construction firm in India. When we refer to a *sector* $S(t^i, c^j)$ - the set of all firms $f^k(t^i, c^j)$ characterized by a task t^i and located in country c^j. Note that the geographical characteristic in our simplified framework captures a number of institutional and other influences, for example, legal framework, variety of capitalism, national economic characteristics etc.

Each firm $f^k(t^i, c^j)$ competes with other firms within $S(t^i, c^j)$ but also with firms in other sectors with different tasks of the production process. The competition between different levels of production defines various market forms and their related types of market power, i.e., oligopoly/monopoly and oligopsony/monopsony. Hence, we can look at market power at a sectoral level such that sectors with the same t^i and different c^j compete in a similar way as firms within a national economy.

In this way, we can extend the different market power notions to a sectoral/geographical level such that sectoral oligopoly (monopoly) refers to a market where few sectors-sellers are (one seller) able to define up to some extent the price at which the goods produced are sold. Along these lines, oligopolists can acquire higher than normal profits or rents by selling to a price higher than the one in a "perfect market". Similarly, sectoral oligopsony (monopsony) refers to a market where few sectors-buyers are (one buyer is) able to exploit producers by paying a lower price for the production of a good.

Within a production chain where the production of a final good includes a number of different tiers which correspond to tasks (t^i), oligopoly and oligopsony power capture the market power asymmetries between different levels of production. Based on this, we can distinguish four different power possibilities for a sector at a tier k with respect to sectors in tiers $k-1$ and $k+1$, which capture the combination of power relations between the two different levels. For example, assume three levels (or tiers) of production. Then,

1) Between levels 2 and 1:
    a) Sectors at 2 have oligopsony power with respect to sectors at 1
    b) Sectors at 1 have oligopoly power with respect to sectors at 2
2) Between levels 2 and 3
    a) Sectors at 3 have oligopsony power with respect to sectors at 2
    b) Sectors at 2 have oligopoly power with respect to sectors at 3

From the above combinations only in the case where 1a and 2b hold, it is rather straightforward to see that sectors on level 2 will be able to exploit their market power to have high profits. Similarly, in the situation where both 1b and 2a hold, sectors on level 2 have no overall market power. However, in the other two cases, it is not clear whether a sector on tier 2 will have market power or not. Furthermore, while in the previous example, sectoral market power at levels 1 and 3 depends on the competition of each with sectors at level 2, sectors at levels 1 and 3 also indirectly compete with each other. Using the same logic in a more realistic production process with more tiers, the sectoral market power will depend on the structure of the whole of the production network and the more complex the structure is the harder it is to identify a sector's relative oligopoly or oligopsony power.

Hence an appropriate measure of market power should take into account the whole production process and also the extent of interactions of each exchange. Put it differently, a measure of sectoral market power should take into account both the direct and indirect effects of the network structure of the global production process and the weight of each of the links. Both of these conditions are satisfied if we use the measure of PageRank centrality. One could argue that degree/strength centrality could equally capture the impacts of the structure of global production on the market power of a specific sector. However, degree/strength centrality concentrates only on the first-tier production relationships between sectors (first-order neighbours). On the other hand, PageRank centrality is able to capture both the direct and indirect linkages formed in complex production systems. In other words, we want to take into account not only the effects of the first-order neighbors/partners of a specific sector, but also the higher-order impacts of all the other sectors in the global economy.

The measure of PageRank centrality has been introduced by the founders of Google search engine, Larry Page and Sergey Brin, who developed, along with Rajeev Motwani and Terry Winograd, a computer algorithm for rating and ranking webpages based on their importance (Page et al., 1999). PageRank centrality is an extension of the eigenvector centrality measure, which is defined as the sum of the links connecting a sector with its neighbors (Newman, 2010). In eigenvector centrality, each link connecting the node under consideration with the neighboring nodes has a different weight, based on the centrality of the latter. That is, the centrality of a node depends not only on the number of links it has established with other nodes, but also on the number of links those other nodes have established with their neighbors, as well. Thus, for example, a sector has higher eigenvector centrality if it is connected to more connected sectors. Mathematically, eigenvector centrality is defined as the sum of the number/weight of links of sector *i*, weighted by the centrality of the neighboring sector *j* with which it has established economic relations. Formally, if A_{ij} is the weighted adjacency matrix for the economic network, eigenvector centrality is defined as:

$$x_i = \frac{1}{\lambda_{max}} \sum_{j=1}^{N} A_{ij} x_j, \tag{1}$$

where, x_i is centrality for sector *i* and x_j the centrality of sector *j* that sells goods and services to sector *i*, while λ_{max} is the maximum eigenvalue of A_{ij}. Thus, sector *i* gains more centrality, if it is connected to more connected sectors, which themselves have higher centralities.

For PageRank centrality, instead of calculating a centrality score proportional to the centrality of neighboring nodes, it scales the effect of those nodes that have a large number of outgoing links. In particular, PageRank is calculated by:

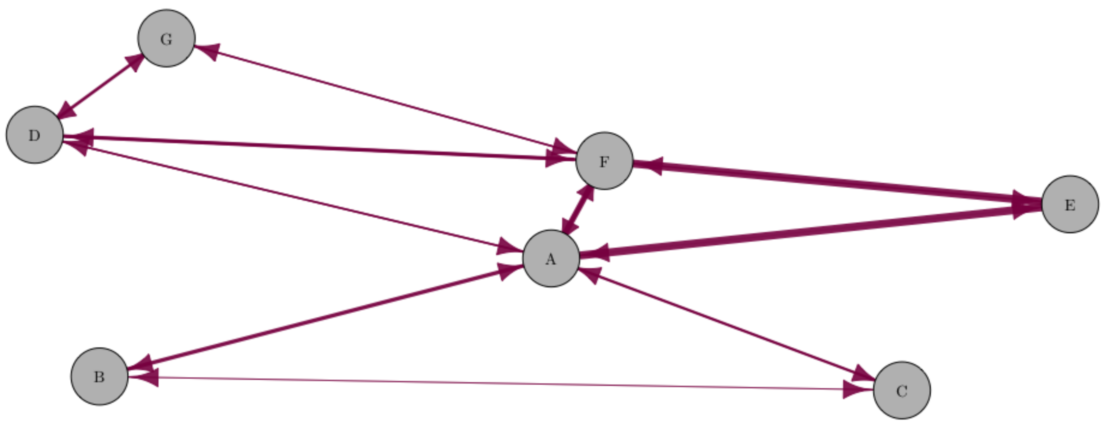
$$x_i = \alpha \sum_{j=1}^{N} A_{ij} \frac{x_j}{deg_j^{out}} + \beta, \tag{2}$$

with x_i and x_j being the centralities of sectors *i* and *j* and α and β the constant parameters. In that way, PageRank centrality gives each sector *i* an equal share of the centrality of high out-strength economic sectors. Moreover, with the inclusion of the constant parameter β assigned to every sector in the economic network, PageRank centrality accounts for those cases of economic sectors that are not well connected with the vast majority of sectors-nodes in an economic network and thus probably assign zero centrality scores to their neighbors.

Regarding our framework, this means that a sector will be highly central in terms of the PageRank centrality if it is connected to highly connected sectors that have gained their importance, although they have a large number of out-going links. Thus, PageRank centrality controls for those cases of economic sectors, which under the eigenvector centrality measure, would have accumulated high scores of centralities, merely since they have established business relationships with large input providers, for example, energy, transportation, and financial intermediation services.

In order to demonstrate the key intuition of this type of sectoral market power, consider the following example. In **Figure 1**, we have plotted a hypothesized production network, with each node expressing an economic sector, and the links connecting them, the value of transactions between them. Sub-graph (b) shows the input-output intermediate goods/services table that functions as the 'recipe' of the production network. Each row shows how much each sector's output has been distributed to the economy and used as inputs. Likewise, each column shows how much inputs each sector will purchase from the other sectors of the economy to produce its respective output. Based on the information of the input-output table, we can calculate, in sub-graph (c), the centralities of every sector in the economy. As we can see, each measure highlights the different properties of the structure of the production network. For instance, with degree centrality, we get the information that the most important (central) sectors are A and F, while sectors B, C, E, and G, share the same amount of positional power. A different picture is given when we consider the measure of strength centrality. Here we observe that the value of transactions between the sectors of a production process matters for their relative positional power. Whereas in the previous example of degree centrality, we could not make any conclusion regarding the relative power of sectors B, C, E and G, now with strength centrality, we have a clear ranking of power asymmetries. On the other hand, PageRank centrality takes into account how central the neighbors of a node are and thus modifies the ranking output of strength centrality analogously.

(a)



Consuming Sectors

Producing Sectors	A	B	C	D	E	F	G
A	0	100	70	50	200	150	0
B	20	0	30	0	0	0	0
C	40	10	0	0	0	0	0
D	50	0	0	0	0	70	80
E	10	0	0	0	0	200	0
F	85	0	0	95	45	0	50
G	0	0	0	35	0	45	0

(b)

Centrality Measures

Economic Sectors	Degree	Strength	PageRank
A	10.00	775.00	0.20
B	4.00	160.00	0.06
C	4.00	150.00	0.08
D	6.00	380.00	0.16
E	4.00	455.00	0.12
F	8.00	740.00	0.27
G	4.00	210.00	0.12

(c)

Figure 1 Centrality Measures in a Hypothesized Production Network

Source: Own Calculation. *Notes:* Sub-graph (a) is the visualization of a production network. Each node represents one of the sectors of our hypothesized economy. The thickness of each link is indicative of the volume/value of the transaction. In sub-graph (b) we have plotted an input-output table of intermediate goods of the hypothesized economy. The rows show the producing sectors and the columns the consuming sectors. Each element of the input-output table expresses the value of transactions between sectors. In sub-graph (c) we have calculated the Degree, Strength and PageRank centralities for every node-sector of the economy. Degree is the most widely used centrality measure, defined as the number of links (connections) a node has with the rest of the nodes. Strength centrality takes into account the volumes of inflows and outflows of inputs and outputs, between sectors in an economy.

4. Empirical Observations

For our investigation we use input-output data from the World Input-Output Database (WIOD). The WIOD (Timmer et al., 2015) results from an international scientific project aiming to combine, harmonize and reconcile economic data from national accounts, national input-output tables and international trade statistics. More specifically, the WIOD project provides time-series data for global input-output tables, giving detailed information about the production processes of national economic sectors on a global scale and data on the components and incomes of the value-added components. This means that additionally to the national-level input-output tables, the WIOD provides information about the international trade flows between economic sectors in the world economy. In other words, using the WIOD, allows us to investigate not only the interconnectedness of an industrial sector with the rest of the economy in a particular country but also the linkages with buyers and suppliers, at the sectoral level, in other countries as well.

All data are structured as a unified global input-output table, with the block diagonal reflecting the national input-output tables. The WIOD comes into two versions, at basic prices in millions of US dollars. The 2013 version covers M = 35 economic sectors (ISIC Rev.3), for N = 40 countries and a proxy for the Rest-of-the-World (RoW), from 1995 to 2011. The 2016 version of the WIOD, on the other hand, covers M = 56 economic sectors (ISIC Rev.4) for N = 44 countries (including an estimate of the RoW), from 2000 to 2014. In this paper, we employ the second version as it is the most recent one and has higher dimensions (more country-sector observations). Given the values of N and M, the database corresponds to 2,408 sectors $S(t^i, c^j)$, which after cleaning for those national sectors that GOS data are not available, we end up with, on average, 2,252 observations. The list of countries and sectors of the WIOD database are shown in the **Appendix**.

<table>
<tr><td colspan="2" rowspan="2"></td><td colspan="7">Consuming Industries</td><td colspan="4">Final Demand</td><td rowspan="2">Total</td></tr>
<tr><td>Sector 1</td><td>Sector 2</td><td>Sector 3</td><td>Sector 4</td><td>…</td><td>Sector n-1</td><td>Sector n</td><td>Consumption</td><td>Investment</td><td>Government Expenditures</td><td>Net Exports</td></tr>
<tr><td>Producing Industries</td><td>Sector 1
Sector 2
Sector 3
Sector 4
…
Sector n-1
Sector n</td><td colspan="7">Intermediate Demand</td><td colspan="4">Final Demand</td><td>Gross Output</td></tr>
<tr><td>Value - Added</td><td>Wages
Profits
Taxes</td><td colspan="7">Value-Added</td><td colspan="4">GDP</td><td></td></tr>
<tr><td colspan="2">Total</td><td colspan="7">Gross Output</td><td colspan="5"></td></tr>
</table>

Figure 2 Schematization of an Input-Output Transactions Table
Source: Adopted by (Miller and Blair, 2009: 3).

The structural composition of the global input-output tables follows the usual structure of the national input-output table, with some important additions. Schematically, a global IOT looks like the one in **Figure 2**, with the four distinct, but interconnected sub-matrices of Intermediate Demand, Final Demand, Value-Added and Total Output. For the purposes of this paper, we focus on the intermediate demand matrix, which presents the productive interdependent relationships among countries and sectors in a world economy, which will be used for the construction of the respective adjacency matrices. In turn, based on the information given by the adjacency matrices, we construct the global production network, with each node representing an economic sector within a country and each link representing inter-country and inter-sectoral linkages. Taking into account these yearly depictions of the global production network, we calculate PageRank centralities for each node, that is, for each observation at the sectoral and national level, using the *igraph* package in *R* (Csardi and Nepusz, 2006).

Table 1 Descriptive Statistics

Year	Variable	Mean	Max	Min	Std. Dev.	Observations
2000	PageRank	0.00040	0.01034	0.00006	0.00061	2250
2001	PageRank	0.00040	0.01082	0.00006	0.00061	2251
2002	PageRank	0.00040	0.01139	0.00006	0.00063	2252
2003	PageRank	0.00040	0.01089	0.00006	0.00064	2251
2004	PageRank	0.00040	0.01076	0.00006	0.00064	2251
2005	PageRank	0.00040	0.01010	0.00006	0.00063	2250
2006	PageRank	0.00040	0.01019	0.00006	0.00063	2249
2007	PageRank	0.00039	0.00985	0.00006	0.00060	2248
2008	PageRank	0.00039	0.00950	0.00006	0.00059	2253
2009	PageRank	0.00039	0.01038	0.00006	0.00060	2253
2010	PageRank	0.00039	0.01045	0.00006	0.00060	2252
2011	PageRank	0.00039	0.00958	0.00006	0.00060	2254
2012	PageRank	0.00038	0.00976	0.00006	0.00060	2253
2013	PageRank	0.00038	0.00981	0.00006	0.00061	2254
2014	PageRank	0.00038	0.01006	0.00006	0.00061	2259
2000	Profit Share	0.00044	0.09133	-0.00565	0.00061	2250
2001	Profit Share	0.00044	0.09872	-0.00452	0.00061	2251
2002	Profit Share	0.00044	0.09858	-0.00362	0.00063	2252
2003	Profit Share	0.00044	0.09124	-0.00323	0.00064	2251
2004	Profit Share	0.00044	0.08429	-0.00279	0.00064	2251
2005	Profit Share	0.00044	0.08365	-0.00319	0.00063	2250
2006	Profit Share	0.00044	0.07984	-0.00301	0.00063	2249
2007	Profit Share	0.00044	0.07685	-0.00248	0.00060	2248
2008	Profit Share	0.00044	0.07354	-0.00485	0.00059	2253
2009	Profit Share	0.00044	0.07980	-0.00220	0.00060	2253
2010	Profit Share	0.00044	0.07439	-0.00205	0.00060	2252
2011	Profit Share	0.00044	0.06977	-0.00202	0.00060	2254
2012	Profit Share	0.00044	0.07117	-0.00208	0.00060	2253

2013	Profit Share	0.00044	0.07109	-0.00198	0.00061	2254
2014	Profit Share	0.00044	0.07280	-0.00197	0.00061	2259

Sources: Own Calculations. *Data*: WIOD.

Additional to the annual input-output tables, the WIOD provides information - among others - about the industry-level capital compensation (Gross Operating Surplus) in each country, which is a generally used proxy of gross profits. Based on this variable, we were able to calculate relative sectoral profit shares, which are computed by dividing the GOS component of the Value-Added of each sector, in each country, over the total amount of GOS generated in the global economy. For example, in order to calculate the relative sectoral profit share of the chemicals sector in China, we divided the gross operating surplus of that sector by the total amount of GOS produced in that year globally. In **Table 1**, we provide the full sample descriptive statistics on our two main variables, namely PageRank centrality and relative sectoral profit-shares.

Our empirical analysis consists of the exploration of two research questions. The first question refers to the statistical distributions that our two main variables follow, namely, PageRank centrality and Global Profit Shares. Do these two variables follow a power-law, another distribution characterized by heavy-tails, or none of the previous? The second empirical question concentrates on the association between the two variables, particularly on identifying the relationship that expresses their association.

A power law is a relationship between two quantities, showing that a relative change in one quantity gives rise to a proportional relative change in the other, independent of the initial size of those quantities. Mathematically, a power-law statistical distribution is expressed as:

$$p(x) \propto x^{-a}, \tag{3}$$

with α a constant parameter known as the scaling parameter of the power-law distribution, which typically lies in the range $2 < \alpha < 3$ (Clauset et al., 2009). According to Clauset, et al. (2009), since very few empirical phenomena obey power laws for all values of x, an important task in the analysis of statistical distributions is the identification of some minimum x_{min} after which the power-law relationship applies.

The literature offers a variety of methods and statistical techniques for identifying whether a statistical distribution follows a power law. Two of the most used ones are a) the Least-Squares Fitting, which, however, generates significant systematic errors (Clauset et al., 2009; Gabaix and Ibragimov, 2011) and b) the Maximum Likelihood fitting along with Goodness-of-Fit testing, using the Kolmogorov-Smirnov statistic and Likelihood Ratio tests (Clauset et al., 2009).

One way, which is very popular in the network theory literature, to apply the first method is to visually examine the presence of a heavy-tail distribution in a sample by plotting the Complementary Cumulative Distribution Function (CCDF) in log-log scales and checking whether it becomes linear in the high-value region (right-tail) (Clauset et al., 2009; Gabaix, 2016). A complementary cumulative distribution function measures the probability of a variable taking values higher than a particular level and is formally defined as:

$$F_x = P(X > x) = 1 - P(X \leq x) \tag{4}$$

Figure 3 shows the CCDF plots for PageRank centrality for each year of the database. Our findings indicate that national sectors are asymmetrically connected to each other, as captured by the distribution of PageRank centrality. The distributional characteristic of our centrality measure is consistent with empirical exercises that investigate similar heavy-tail properties in real-life networks (Barabási, 2016; Newman, 2010), as well as production networks (Cerina et al., 2015; Tsekeris, 2017). Hence our plots indicate the possibility of the presence of a power-law distribution for most years.

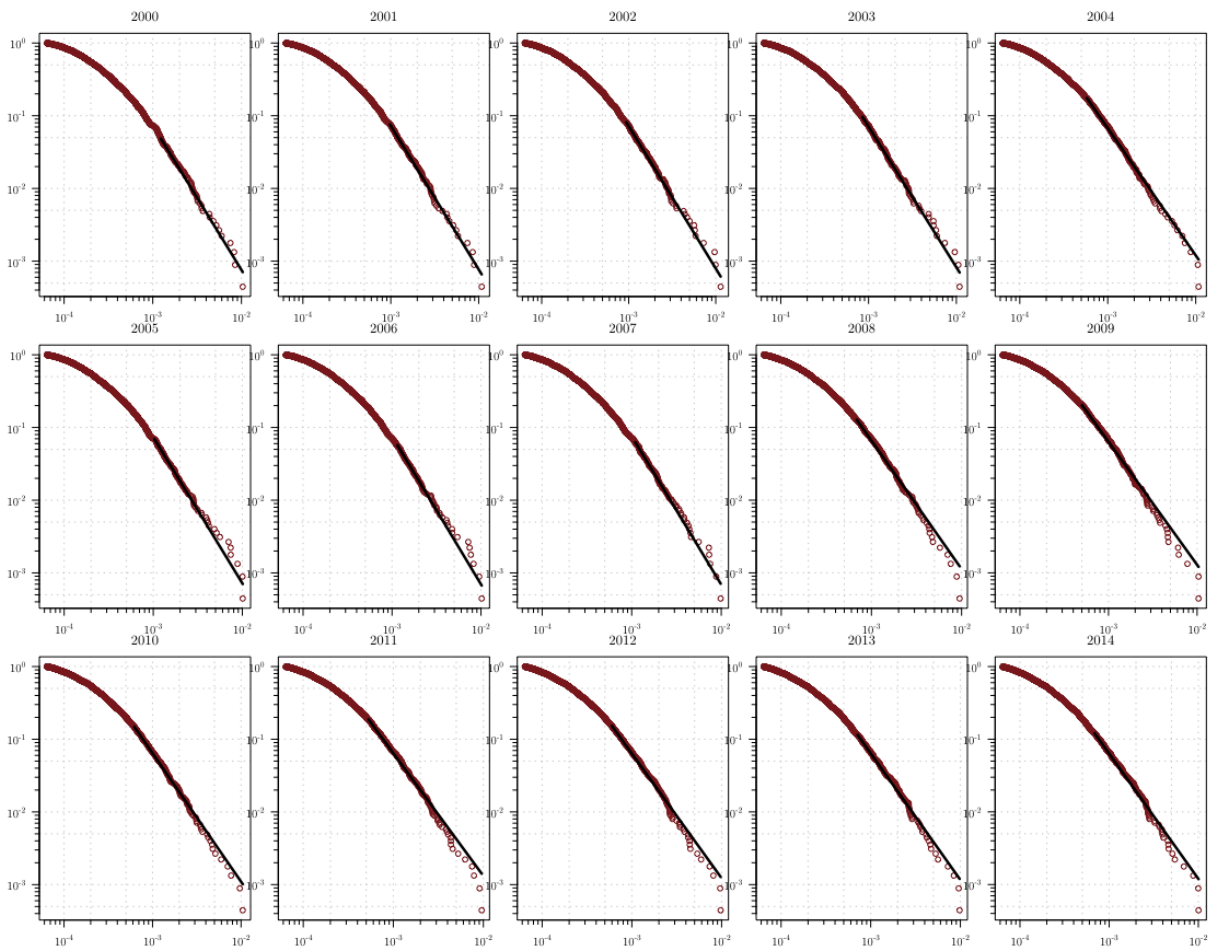


Figure 3 Distributions of PageRank Centrality (CCDF)
Source: Own Calculation. Data: WIOD. *Note*: Plots in log-log scales.

Similarly, in **Figure 4**, we observe the right-skewed distribution of Profit Shares in the world economy, which implies how unequal the global distribution of profits among national sectors is, among both countries and sectors. Here the linear part, thus the indication of a power-law distribution appears more clearly than in the previous figure and in most graphs the linear part is longer.

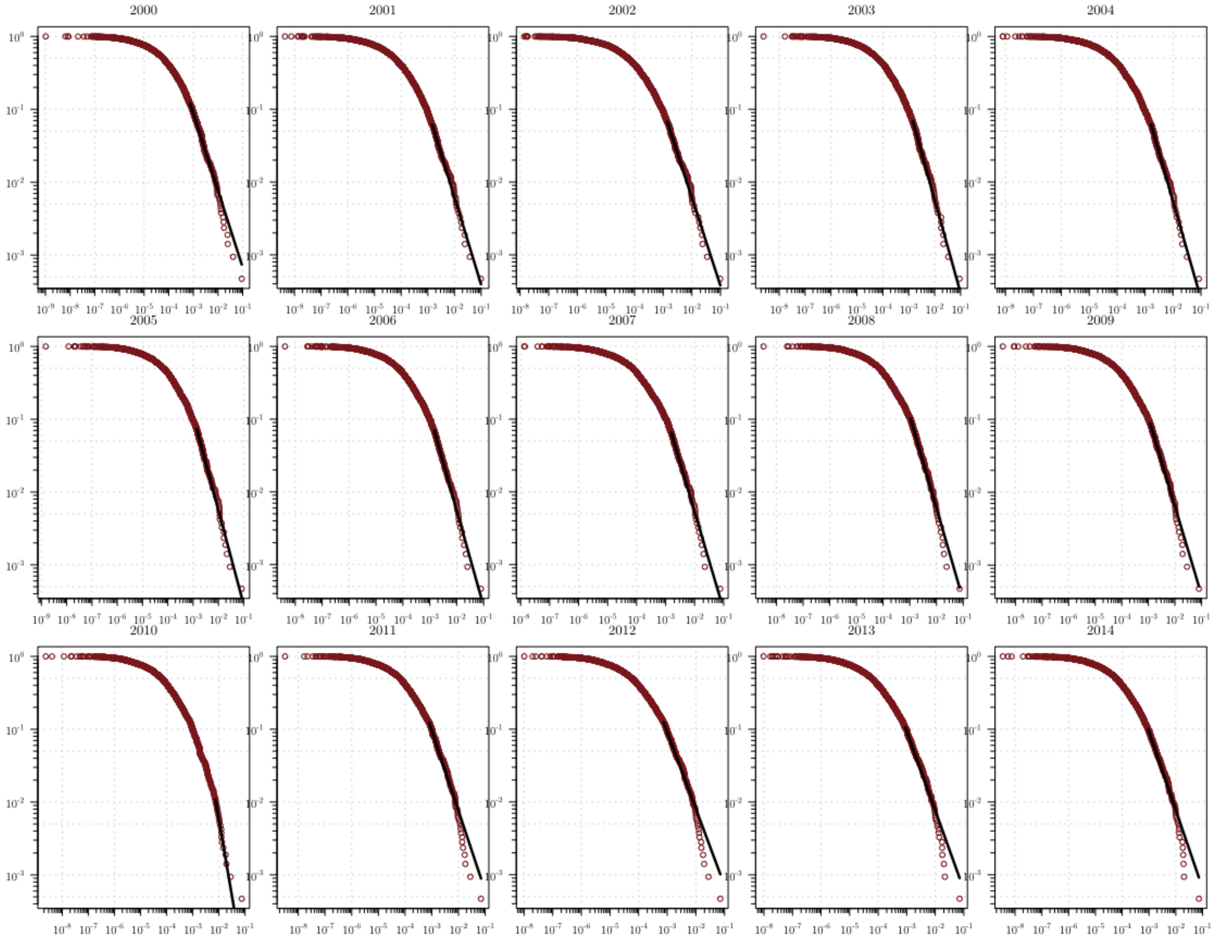


Figure 4 Distributions of Profit Shares (CCDF)
Source: Own Calculation. Data: WIOD. *Note*: Plots in log-log scales.

However, the literature has concluded that the visual inspection of CCDF plots and the OLS method are prone to systematic errors and biases (Clauset et al., 2009; Gabaix and Ibragimov, 2011), we also applied the technique proposed by Clauset, et al. (2009). In their paper, Clauset, et al. (2009) propose a statistical framework for identifying power-law behavior in empirical data that combines Maximum Likelihood fitting with Goodness-of-Fit tests, based on the Kolmogorov-Smirnov (KS) statistic and Likelihood Ratio (LR) tests. The procedure develops into three steps, which we describe in detail below. For applying this method, we used the statistical package *poweRlaw* in *R*, which provides built-in functions for each step (Gillespie, 2015).

The first step in the process is to estimate the lower bound of the x_{min} and the scaling parameter α. To do so, we employ a maximum likelihood estimator and we minimize the distance between our data and the fitted model CDF, which is measured with a KS statistic. In practice, we initially set x_{min} to the smallest value of our dataset and then compare the empirical and theoretical CDF, using the distance function from the KS statistic. We continue the same process, setting each x of our dataset as x_{min} iteratively, and finally choose the value with the lowest KS statistic. Having found the right x_{min} we re-estimate the correct scaling parameter α. In **Table 2**, we show the results of our estimation exercise, along with the minimum value of the KS statistic.

Table 2 Estimation of X_{min} and Scaling Parameter α

	PageRank Centrality			Relative Profit-Share		
Year	KS	x_{min}	α	KS	x_{min}	α
2000	0.04272	0.00123	2.98743	0.04953	0.00073	2.05484
2001	0.03350	0.00098	2.97406	0.04692	0.00147	2.19997
2002	0.03165	0.00094	2.95773	0.04226	0.00138	2.21208
2003	0.02940	0.00085	2.93353	0.04663	0.00144	2.28229
2004	0.02893	0.00058	2.74943	0.03745	0.00164	2.33913
2005	0.02930	0.00103	3.01008	0.03716	0.00139	2.29855
2006	0.03238	0.00115	3.03629	0.02708	0.00146	2.31586
2007	0.03754	0.00110	3.04093	0.03860	0.00157	2.34903
2008	0.04074	0.00069	2.76785	0.03024	0.00107	2.26232
2009	0.03396	0.00050	2.69200	0.03694	0.00117	2.21804
2010	0.02960	0.00062	2.76664	0.04478	0.00734	3.09707
2011	0.02987	0.00053	2.68843	0.04312	0.00080	2.10130
2012	0.03050	0.00060	2.71344	0.04298	0.00074	2.05410
2013	0.03196	0.00072	2.74062	0.04518	0.00090	2.08827
2014	0.03076	0.00069	2.72269	0.04035	0.00093	2.07446

Sources: Own Calculations. *Data*: WIOD.

In the second step of the process, we need to test the power-law hypothesis, using a *goodness-of-fit* test, with a bootstrap procedure. In particular, we need to generate multiple datasets with the parameters estimated in the previous step and then re-run the estimation process. If the *p-value* is greater than 10% significance level (*p-value* > 0.1), then we can safely say that we cannot rule out the power law model. We performed the second step, running 1,000 bootstrap simulations for each of our variables, the results of which are presented in **Table 3**. Based on the *p-values* we cannot reject the Null hypothesis that the sample comes from a power-law distribution.

Table 3 Estimation of X_{min} and Scaling Parameter α

	PageRank Centrality		Relative Profit-Share	
Year	KS	p-value	KS	p-value
2000	0.043	0.515	0.050	0.023
2001	0.034	0.697	0.047	0.223
2002	0.032	0.726	0.042	0.360
2003	0.029	0.703	0.047	0.289
2004	0.029	0.384	0.037	0.800
2005	0.029	0.916	0.037	0.639
2006	0.032	0.811	0.027	0.982
2007	0.038	0.568	0.039	0.590
2008	0.041	0.049	0.030	0.805
2009	0.034	0.092	0.037	0.517
2010	0.030	0.435	0.045	0.852
2011	0.030	0.255	0.043	0.123
2012	0.031	0.319	0.043	0.103

2013	0.032	0.327	0.045	0.104
2014	0.031	0.416	0.040	0.252

Sources: Own Calculations. *Data*: WIOD.

The third step asks for the direct comparison of our power-law model with a family of alternative statistical distributions, like for example the exponential or the log-normal. We can do that with the Likelihood Ratio Test (LR-test), which estimates the likelihood of the data under two competing distributions. Taking the logarithm of the ratio of the two likelihoods we will be able to evaluate the sign and thus which distribution fits better our data. The latter sign is statistically significant if it is sufficiently away from zero. Vuong (1989) proposed a method with which the standard deviation of log-LR is estimated and the *p-value* evaluated against the decided significance level (*p-value* < 0.1). In **Table 4**, we present the results of the third step showing the values of the LR test, along with the respective p-values, for the PageRank centrality and relative profit-shares data. Comparing the power law distributions with three alternative distributions, we find evidence that the power law describes better our dataset compared to Weibull and Exponential. With respect to Log-Normal, we didn't find statistically significant *p-values*, so we are unable from the Vuong's (1989) LR test to determine whether power-law or log-normal better fits our data. Notwithstanding, we can infer that our data follow a heavy-tail distribution.

Table 4 Likelihood Ratio Tests for Direct Comparisons of Distributions

	PageRank Centrality						Relative Profit-Shares					
	Exponential		Log-Normal		Weibull		Exponential		Log-Normal		Weibull	
Year	LR	p-value	LR	p-value	LR	p-value	LR	p-value	LR	p-value	LR	p-value
2000	1.63	0.10	-0.41	0.69	5.07	0.00	2.79	0.01	-1.12	0.26	1.33	0.18
2001	2.18	0.03	-0.39	0.69	10.38	0.00	2.21	0.03	-0.40	0.69	3.27	0.00
2002	2.52	0.01	-0.22	0.83	2.41	0.02	2.22	0.03	-0.41	0.68	4.84	0.00
2003	2.79	0.01	-0.21	0.83	6.21	0.00	2.30	0.02	-0.24	0.81	5.05	0.00
2004	3.19	0.00	-0.76	0.45	18.13	0.00	2.15	0.03	-0.20	0.84	1.88	0.06
2005	2.93	0.00	0.03	0.98	9.25	0.00	2.22	0.03	-0.36	0.72	5.49	0.00
2006	2.71	0.01	0.01	0.99	8.29	0.00	2.11	0.03	-0.38	0.70	1.43	0.15
2007	2.34	0.02	-0.21	0.84	8.40	0.00	1.89	0.06	-0.42	0.68	1.49	0.14
2008	2.21	0.03	-1.10	0.27	3.61	0.00	2.35	0.02	-0.65	0.51	1.78	0.07
2009	2.92	0.00	-1.18	0.24	6.77	0.00	2.13	0.03	-0.75	0.45	12.34	0.00
2010	2.77	0.01	-0.83	0.41	4.58	0.00	1.48	0.14	0.10	0.92	1.24	0.21
2011	3.07	0.00	-1.09	0.27	-1.75	0.08	2.52	0.01	-1.30	0.19	3.31	0.00
2012	2.73	0.01	-0.97	0.33	3.12	0.00	2.60	0.01	-1.47	0.14	22.66	0.00
2013	2.34	0.02	-0.91	0.36	3.49	0.00	2.38	0.02	-1.24	0.21	7.80	0.00
2014	2.36	0.02	-0.93	0.35	3.51	0.00	2.20	0.03	-1.34	0.18	0.61	0.54

Sources: Own Calculations. *Data*: WIOD.

Consequently, we have so far ruled out the possibility of Weibull and Exponential distributions describing our data better than a power law distribution, and we cannot definitely choose among power-law and a log-normal.

Next, we plot (**Figure 5**) the logs of the two variables and observe a clear correlation between the two variables possibly indicating a power law relationship. In order to get a more concrete idea regarding the relationship of the two variables, we regress the logarithms of the two variables, and find a statistically significant relationship with an exponent parameter being on average around 2[1]. We estimate the exponent of the relationship *Profits ~ PageRank*$^{\alpha}$, by regressing *log(Profits) ~ Constant +* α *log(PageRank)*, with Profits being the sectoral relative profits and PR the PageRank centrality. The results of the regressions are gathered in **Table A-1** in the **Appendix**.

But what does it mean for the PageRank centrality to be related to the relative sectoral relative profits with a power-law relationship? In our context, PageRank centrality captures the relative market power at the sectoral level, taking into account the whole structure of global production, whereas the sectoral relative profits are the proportion of profits that each sector accrues compared to the total global portion of profits. The power-law relationship between the two implies that a relative change in the quantity of sectoral market power (PageRank) will give rise to a proportional relative change in the quantity of sectoral relative profits, independent of the initial size of each variable. In other words, if the logarithm of market power increases by 1%, then the logarithm of sectoral relative profits will increase 2 times more.

Given that higher market power leads, on average, to higher profits, then our empirical observation of a power-law relationship between PageRank centrality and sectoral relative profits, provides strong evidence for the appropriateness of such a measure. Moreover, the heavy-tailed relationship between sectoral centrality and sectoral relative profits implies a strong sectoral centralization incentive in global production. In other words, irrespective of whether we observe a high or low distribution of relative profits in a particular global sector, the latter has a strong incentive to become more central sectors with respect to global production structures and thus acquire proportionally higher profits.

[1] For details see Table 1 in the Appendix.

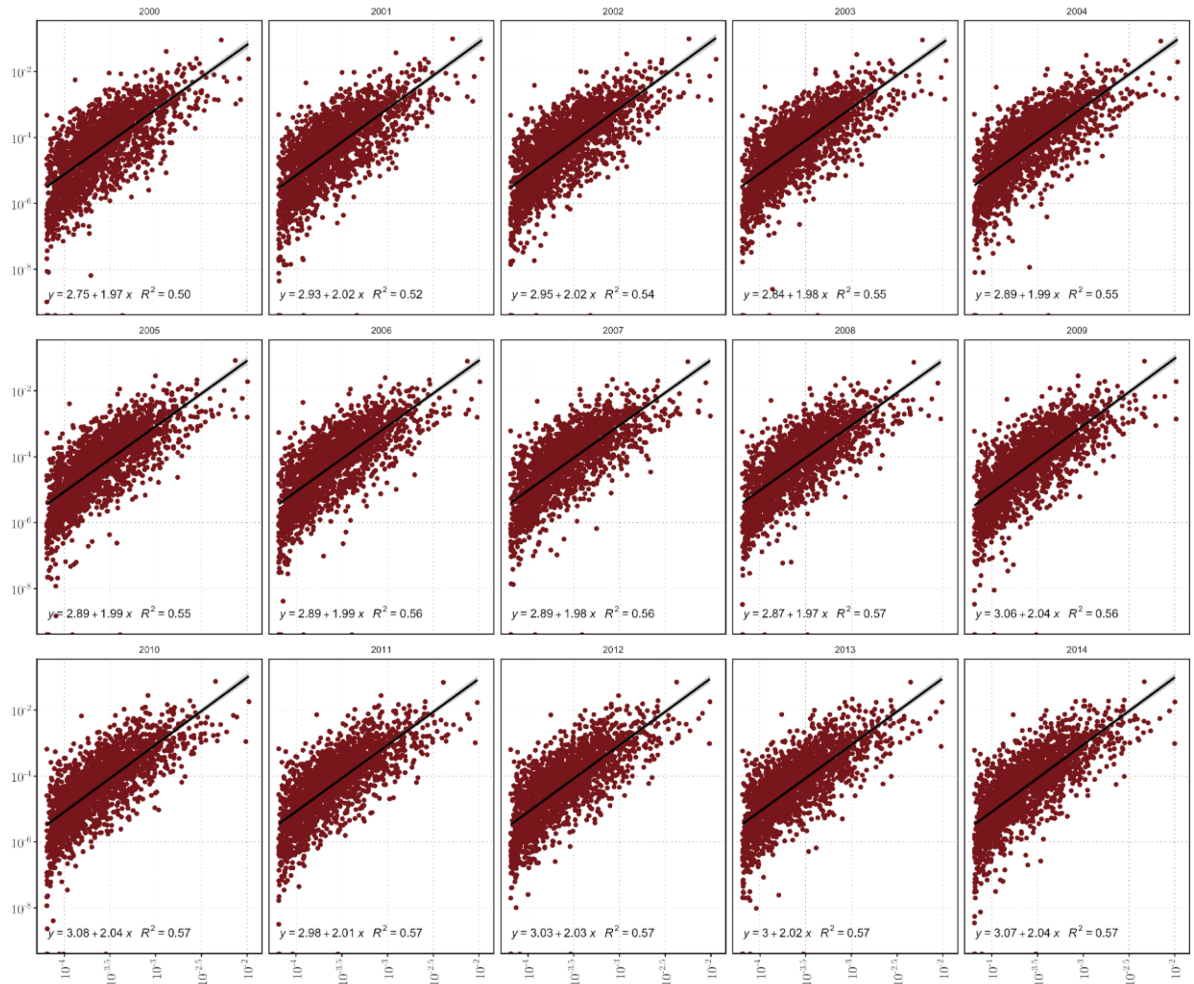


Figure 5 Power Law Relationship between PageRank and Profit Shares (log-log)

Source: Own Calculation. *Data*: WIOD. *Notes*: Plots in log-log scales. In order to estimate the exponent of the relationship $Profit\ Shares \sim PageRank^{a}$, we run the regression $log\ PS\ = Constant + a \cdot log\ PR$, with PS being the Profit Shares and PR the PageRank centrality. The results of the regression are in Table A-1 of the Appendix.

Accounting for cross-country and cross-sectoral heterogeneities is a task beyond the scope of this paper. However, in **Figure 6** and **Figure 7**, we present the plots of the logs of the relative Profit-Shares and PageRank centrality, per country and per sector, respectively. What these graphs suggest is that the power-law relationship between the sectoral market power, measured by PageRank centrality, and relative profitability, measured by profit-shares, holds across countries and sectors. For the sake of completeness, in the **Appendix**, we present the regression results for all countries and sectors across time.

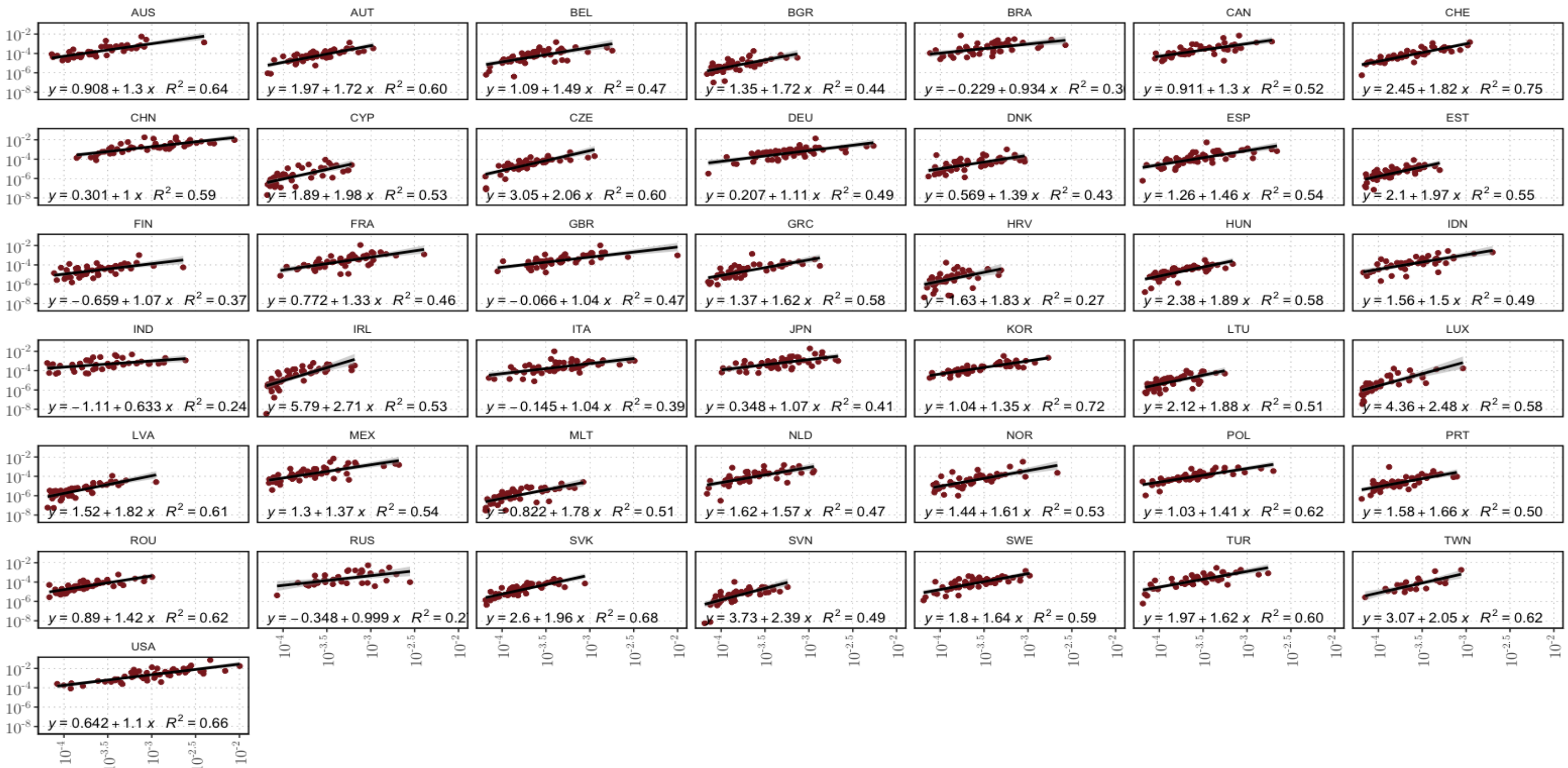


Figure 6 Power Law Relationship between PageRank and Profit Shares (log-log), for Countries

Source: Own Calculation. *Data*: WIOD. *Notes*: Plots in log-log scales. In order to estimate the exponent of the relationship $Profit\ Shares \sim PageRank^{a}$, we run the regression $log\ PS\ = Constant + a \cdot log\ PR$, with PS being the Profit Shares and PR the PageRank centrality. The results of the regression are in Table A-XX of the Appendix.

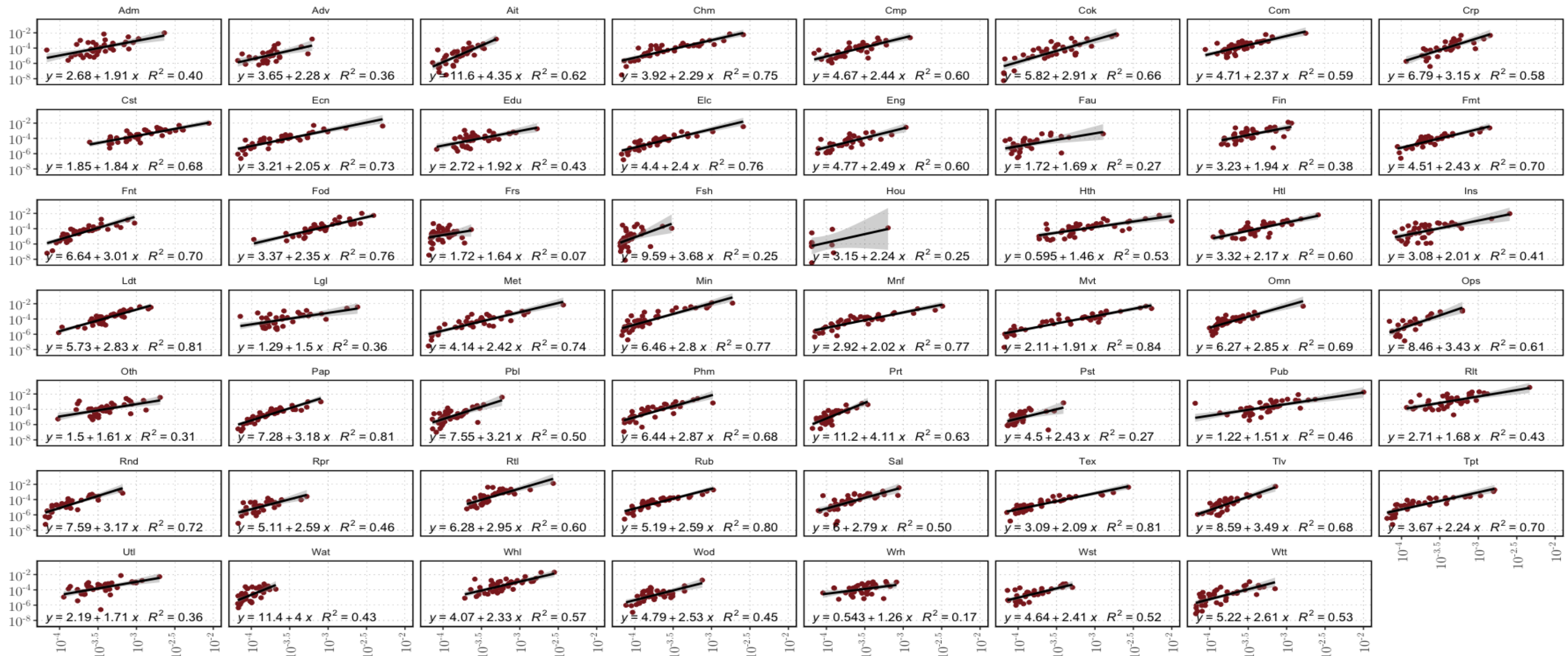


Figure 7 Power Law Relationship between PageRank and Profit Shares (log-log), for Sectors

Source: Own Calculation. *Data*: WIOD. *Notes*: Plots in log-log scales. In order to estimate the exponent of the relationship $Profit\ Shares \sim PageRank^{a}$, we run the regression $log\ PS\ = Constant + a \cdot log\ PR$, with PS being the Profit Shares and PR the PageRank centrality. The results of the regression are in Table A-XX of the Appendix.

5. Conclusion

The notion of power and the different forms it may take, is central in a number of frameworks that analyze global production. However, their respective focus has been on firms without properly taking into account neither the fact that firms belong to national sectors, and hence sectoral power is a possibly important factor to take into account, nor the possible effects of the network structure of global production. Apart from the significance on a theoretical level, given the availability of sectoral level input-output data, a sectoral analysis is able to allow for empirical investigation of power, while taking into account the complexity of global production processes.

The present paper contributes to this direction on both a theoretical and an empirical level. We first argued that sectoral market power should consider the total of the global production structure and that this can be done by using the PageRank centrality measure. Then, using input-output data, we provided a preliminary investigation of the properties of PageRank centrality and its relationship with relative sectoral profits. In sum, we find that the distribution of both variables has heavy tails and evidence of power-law distributions and also some evidence showing a power-law relationship between the two variables.

Moreover, our paper contributes to the literature that follows the GVCs/GPNs framework (Coe and Yeung, 2015; Gereffi, 2018; Henderson et al., 2002) by highlighting the importance of sectoral level analysis in global production and introducing a measure of market power building on relevant network centrality concepts. These approaches talk about conflicts between actors within supply chains, but they usually underestimate the need for an index that properly captures these conflicts. On an empirical level, based on a dataset of global input-output tables, we observe that the sectoral relative profits and the PageRank centrality across sectors have heavy tails, and the graphs indicate power-law distributions. The distribution of the relative profits highlights that a small number of sectors have a relatively high share of profits. Similarly, the (PageRank) centrality of most sectors is low. At the same time, for some, it is relatively high. The regression analysis assessing the power-law relationships between sectoral relative profits and centrality shows an exponent close to 2. This empirical observation demonstrates that a strong centralization incentive exists for economic sectors, globally, and hence for the firms that belong to each of these.

Our work can be extended in a number of directions. Our approach can be extended to match the bipartite network structure out of global WIOD input-output tables by breaking down the original network into two, allowing a network projection at the sectoral and country level. Given that our results are for national sectors, such a structure will enable several possible geography-related questions to be raised and addressed. For example, which are the countries and regions where most central sectors are located? Would the same observations still hold if the analysis was conducted on a global level where national sectors would be aggregated? How will the concept of power in our network be connected to macroeconomic performance? What is the economic impact of core sectors?

While our empirical investigation is preliminary, our paper sets the ground for further and more complete analysis regarding the importance of PageRank centrality as a measure of sectoral market power in global production. There are a number of possible research questions in this direction. For example, analyze in more detail the different power-law properties and/or the relationship between PageRank and various measures of sectoral profitability. While a sectoral level analysis can provide both theoretical and empirical insights, keeping in mind that sectors are sets of firms, it is also important to analyze the relationship between firms within key sectors. For example, one other direction of future research is to see whether there are different patterns of firms' profits within sectors with very different centralities.

References

Acemoglu D, Carvalho VM, Ozdaglar A, et al. (2012) The Network Origins of Aggregate Fluctuations. *Econometrica* 80(5): 1977–2016.

Amador J and Cabral S (2017) Networks of Value-added Trade. *World Economy* 40(7): 1291–1313.

Antràs P and Chor D (2018) *On the Measurement of Upstreamness and Downstreamness in Global Value Chains*. *NBER Working Paper Series*. NBER Working Paper Series 24185. Cambridge, MA.

Antràs P, Chor D, Fally T, et al. (2012) Measuring the Upstreamness of Production and Trade Flows. *American Economic Review: Papers & Proceedings* 102(3): 412–416.

Axtell RL (2001) Zipf Distribution of U.S. Firm Sizes. *Science* 293(5536): 1818–1820.

Barabási A-L (2016) *Network Science*. Cambridge, UK: Cambridge University Press.

Baran PA and Sweezy PM (1966) *Monopoly Capital: An Essay on the American Economic and Social Order*. *Monthly Review Press*. Monthly Review Press.

Bottazzi G, Coad A, Jacoby N, et al. (2011) Corporate growth and industrial dynamics: evidence from French manufacturing. *Applied Economics* 43(1): 103–116.

Bottazzi G, Pirino D and Tamagni F (2015) Zipf law and the firm size distribution: a critical discussion of popular estimators. *Journal of Evolutionary Economics* 25(3): 585–610.

Calvino F, Criscuolo C, Menon C, et al. (2018) Growth volatility and size: A firm-level study. *Journal of Economic Dynamics and Control* 90: 390–407.

Cerina F, Zhu Z, Chessa A, et al. (2015) World input-output network. *PLoS ONE* 10(7): e0134025.

Clauset A, Shalizi CR and Newman MEJ (2009) Power-Law Distributions in Empirical Data. *SIAM Review* 51(4): 661–703.

Coe NM and Yeung HW (2015) *Global Production Networks: Theorizing Economic Development in an Interconnected World*. Oxford University Press.

Coe NM, Dicken P and Hess M (2008) Global production networks: Realizing the potential. *Journal of Economic Geography* 8(3): 271–295.

Contreras MGA and Fagiolo G (2014) Propagation of Economic Shocks in Input-Output Networks: A Cross-Country Analysis. *Physical Review E* 90(06812): 1–9.

Dallas MP, Ponte S and Sturgeon TJ (2019) Power in global value chains. *Review of International Political Economy* 26(4): 666–694. DOI: 10.1080/09692290.2019.1608284.

De Masi G and Ricchiuti G (2020) From FDI network topology to macroeconomic instability. *Journal of Economic Interaction and Coordination* 15(1): 133–158. DOI: 10.1007/s11403-019-00275-0.

Dicken P, Kelly PF, Olds K, et al. (2001) Chains and Networks, Territories and Scales: Towards a Relational Framework for Analysing the Global Economy. *Global Networks* 1(2): 89–112.

Fagiolo G, Reyes J and Schiavo S (2009) World-Trade Web: Topological Properties, Dynamics,

and Evolution. *Physical Review E* 79(036115): 1–19.
Feenstra RC (1998) Integration of Trade and Disintegration of Production in the Global Economy. *Journal of Economic Perspectives* 12(4): 31–50.
Gabaix X (2011) The Granular Origins of Aggregate Fluctuations. *Econometrica* 79(3): 733–772.
Gabaix X (2016) Power Laws in Economics: An Introduction. *Journal of Economic Perspectives* 30(1): 185–206.
Gabaix X and Ibragimov R (2011) Rank — 1/2: A Simple Way to Improve the OLS Estimation of Tail Exponents. *Journal of Business & Economic Statistics* 29(1). American Statistical Association: 24–39. Available at: http://www.jstor.org/stable/25800776.
Gabaix X and Ioannides YM (2004) The Evolution of City Size Distributions. In: Henderson JV and Thisse J-FBT-H of R and UE (eds) *Cities and Geography*. Amsterdam: Elsevier, pp. 2341–2378.
Galanis G and Kumar A (2020) A Dynamic Model of Global Value Network Governance. *Environment and Planning A: Economy and Space* 0(0): 1–20.
Gereffi G (1994) The Organization of Buyer-Driven Global Commodity Chains: How US Retailers Shape Overseas Production Networks. In: Gereffi G and Korzeniewicz M (eds) *Commodity Chains and Global Capitalism*. Westport: Praeger Publishers, pp. 95–122.
Gereffi G (2018) *Global Value Chains and Development. Redefining the Contours of 21st Century Capitalism*. Cambridge University Press.
Gereffi G, Humphrey J and Sturgeon TJ (2005) The Governance of Global Value Chains. *Review of International Political Economy* 12(1): 78–104.
Giammetti R, Russo A and Gallegati M (2020) Key sectors in input–output production networks: An application to Brexit. *The World Economy* 43(4): 840–870. DOI: 10.1111/twec.12920.
Gibbon P, Bair J and Ponte S (2008) Governing Global Value Chains: An Introduction. *Economy and Society* 37(3): 315–338.
Gillespie CS (2015) Fitting Heavy Tailed Distributions: The poweRlaw Package. *Journal of Statistical Software* 64(2): 1–16. DOI: 10.18637/jss.v064.i02.
Hausmann R and Hidalgo CA (2011) The Network Structure of Economic Output. *Journal of Economic Growth* 16(4): 309–342.
Henderson J, Dicken P, Hess M, et al. (2002) Global production networks and the analysis of economic development. *Review of International Political Economy* 9(3): 436–464.
Hsu W (2012) Central Place Theory and City Size Distribution. *The Economic Journal* 122(563): 903–932.
Hummels D, Ishii J and Yi KM (2001) The nature and growth of vertical specialization in world trade. *Journal of International Economics* 54(1): 75–96.
Johnson RC (2018) Measuring Global Value Chains. *Annual Review of Economics* 10: 207–236.
Kalecki M (1938) The Determinants of Distribution of the National Income. *Econometrica* 6(2). [Wiley, Econometric Society]: 97–112. DOI: 10.2307/1907142.
Kalecki M (1968) *Theory of Economic Dynamics*. New York: Monthly Review Press.
Koopman R, Wang Z and Wei SJ (2012) Estimating Domestic Content in Exports when Processing Trade is Pervasive. *Journal of Development Economics* 99(1): 178–189.
Kumar A (2020) *Monopsony Capitalism: Power and Production in the Twilight of the Sweatshop Age*. Cambridge University Press.
Lavoie M (2014) *Post-Keynesian Economics: New Foundations*. Cheltenham, UK: Edward Elgar Publishing.

Mahutga MC (2014) Global models of networked organization, the positional power of nations and economic development. *Review of International Political Economy* 21(1): 157–194.

Mas-Colell A, Whinston MD and Green JR (1995) *Microeconomic Theory*. Oxford, UK: Oxford University Press.

McNerney J, Savoie C, Caravelli F, et al. (2022) How production networks amplify economic growth. *Proceedings of the National Academy of Sciences* 119(1). DOI: 10.1073/pnas.2106031118.

Milberg W and Winkler D (2013) *Outsourcing Economics: Global Value Chains in Capitalist Development*. Cambridge University Press.

Miller RE and Blair PD (2009) *Input-Output Analysis: Foundations and Extensions*. *Cambridge University Press*. 2nd ed. Cambridge University Press.

Newman MEJ (2010) *Networks. An Introduction*. Oxford University Press.

Page L, Brin S, Motwani R, et al. (1999) *The PageRank Citation Ranking: Bringing Order to the Web*. Standford, California.

Rutherford T and Holmes J (2008) 'The flea on the tail of the dog': power in global production networks and the restructuring of Canadian automotive clusters. *Journal of Economic Geography* 8(4): 519–544.

Sawyer MC (1985) An Introduction to Kalecki and His Ideas. In: *The Economics of Michał Kalecki*. London, UK: Macmillan Education UK, pp. 1–19.

Serrano MÁ and Boguñá M (2003) Topology of the world trade web. *Physical Review E* 68(1): 015101.

Shaikh A (2016) *Capitalism: Competition, Conflict, Crises*. Oxford University Press.

Shepherd JM and Shepherd WG (2003) *The Economics of Industrial Organization*. 5th ed. Waveland Press.

Su H-L (2020) On the city size distribution: A finite mixture interpretation. *Journal of Urban Economics* 116: 103216.

Timmer MP, Dietzenbacher E, Los B, et al. (2015) An Illustrated User Guide to the World Input-Output Database: the Case of Global Automotive Production. *Review of International Economics* 23(3): 575–605.

Tonts M, Plummer P and Taylor M (2012) Power, enterprise and employment growth in Australian small- and medium-sized manufacturing firms. *Journal of Economic Geography* 12(6): 1239–1266.

Tsekeris T (2017) Global value chains: Building blocks and network dynamics. *Physica A: Statistical Mechanics and its Applications* 488: 187–204.

Varian HR (1992) *Microeconomic Analysis*. 3rd ed. New York, NY: W.W. Norton & Company.

Vuong QH (1989) Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses. *Econometrica* 57(2): 307. DOI: 10.2307/1912557.

Xu M, Allenby BR and Crittenden JC (2011) Interconnectedness and Resilience of the US Economy. *Advances in Complex Systems* 11(5): 649–672.