COMPLEX NETWORK ANALYSIS UNCOVERS THE RECONFIGURATION OF THE MEXICAN ECONOMY[1]

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ABSTRACT

We use input-output tables and complex network analysis to identify changes in the production structure of the Mexican economy and uncover whether the economic system has experienced a reconfiguration. Results show changes in the structural properties of the economy. Intermediate demands were best described by the logistic distribution with changes in the estimated parameters. The number of intersectional relations increased resulting in higher densities of the production network. In general, sectors presented more and stronger connections; but manufacturing sectors behaved differently. They decreased the number of connections as input buyer and slightly increased the number of connections as input suppliers. There is evidence that manufacturing sectors were more affected in terms of the strength of the connections than the number. Finally, authority and hub scores show that a few sectors emerged as most important.

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Therefore, complex network analysis uncovered a reconfiguration of the Mexican economy but not a structural change.
Keywords: Reconfiguration, structural properties, production network, complex network analysis.
JEL Classification: C67, D57, D85, O14.

ANÁLISIS DE REDES COMPLEJAS DESCUBRE
LA RECONFIGURACIÓN DE LA ECONOMÍA MEXICANA

RESUMEN

Utilizamos matrices insumo-producto y aplicamos un análisis de redes complejas para identificar cambios en la estructura productiva de México y poder determinar si la economía mexicana ha experimentado una reconfiguración. Los resultados muestran que la economía ha experimentado cambios en su estructura productiva que dan evidencia de una reconfiguración. La distribución de demandas intermedias fue mejor descrita por una logística, pero su localización y escala cambiaron convirtiéndola en una distribución más plana. El número de conexiones de los sectores aumentó incrementando la densidad de la red. En general, el número de conexiones y sus fortalezas aumentaron. Sin embargo, los sectores manufactureros se comportaron diferente. Estos sectores disminuyeron su número de conexiones como compradores de insumos y ligeramente incrementaron su número de conexiones como proveedores. Existe evidencia de que se vieron más afectados en términos de la fortaleza de las conexiones que del número. Finalmente, la organización jerárquica de sectores cambió. Estos resultados dan evidencia de un proceso de desindustrialización, pero no de un cambio estructural.
Palabras clave: industrialización, propiedades estructurales, red productiva, análisis de redes complejas
Clasificación JEL: C67, D57, D85, O14.

1. INTRODUCTION

The analysis of the properties of the structure of the economy is essential to reveal a reconfiguration in the productive system. The nature of this reconfiguration could be the result of an industrialization or a deindustrialization process. These processes are key in a development strategy of a country. Frequently, industrialization has been studied as contributions of manufacturing sectors on Gross Domestic Product (GDP), value added, final production, or employment. However, relying on these contributions may mislead researchers and policy makers to conclude that a country has experienced an industrialization or deindustrialization process without analyzing changes in the entire structure of the economy. In this paper we are interested on identifying changes in the configuration of the Mexican economic system through the properties of the production network.

In a Kaldorian perspective, manufacturing output is put as a main driver of economic growth and a positive causal relationship is established between the size of the manufacturing sector and the growth of labour productivity (Kaldor, 1967; Sato and Kuwamori, 2024). Therefore, in this perspective deindustrialization would imply a decrease in the manufacturing output growth and manufacturing shares of GDP and employment (Kim and Lee, 2014). According to Rodrik (2016) deindustrialization refers to the experience of advanced economies of a decreasing manufacturing share of employment. Comparably, developing economies may experience a different deindustrialization trajectory. Deindustrialization processes and the importance of the manufacturing sectors are highly relevant problems to address. An early deindustrialization could have negative effects on economic growth (Rodrik, 2016). Consequently, deindustrialization has been the focus of many research.

Rodrik discusses the deindustrialization experiences in low and middle-income countries and called it the "premature deindustrialization". In this process, countries such as Mexico experienced falling manufacturing shares in manufacturing employment and real value added. Rodrik gives evidence that developing countries are reaching the turning point in the U-shape path over the course of development much sooner at lower income levels. These type of countries are turning into service economies (Rodrik, 2016; Aiginger and Rodrik, 2020). Sato and Kuwamori (2024) discuss about the mechanism behind premature deindustrialization, its effects and alternatives for economic growth. Authors examine the relation between manufacturing output (value added), employment ratio and income (GDP per capita) following the work of Rodrik. Authors found a positive correlation between maximum manufacturing shares and corresponding incomes (Sato and Kuwamori, 2024). To confirm premature deindustrialization authors estimated for Organisation for Economic Co-operation and Development (OECD) countries the effects on manufacturing share of population and GDP per capita. Estimations found an inverted U-shape between income and manufacturing share (Sato and Kuwamori, 2024). Araujo *et al.* (2021) investigate the main determinants of deindustrialization using panel data analysis for a group of countries from 1970 to 2017. Authors found different effects on manufacturing value added depending on the level of development of the countries. The degree of openness positively affects the manufacturing value added in developed economies. On the contrary, for developing countries the effect was negative.

Dosi and coauthors perform a cross country analysis for 73 countries from 1963 to 2015 to study deindustrialization processes on employment and value added looking at technological characteristics of industrial sectors. Authors found an uneven process of deindustrialization not presenting any inverted U-shape and the emergence of four clusters with different degrees of diversification (Dosi, Riccio and Virgilio, 2021). Authors highlight the relevance of the manufacturing sector for economic development and recall that manufacturing sectors are the engine of growth according to the "Hirschman-Prebisch" approach. Van Neuss (2018) presents different channels through which deindustrialization may take place as a consequence of structural change: Non-nomothetic preferences, technology, input-put and outsourcing, and international trade. Authors perform an econometric analysis based on panel data for 15 OECD countries that correspond to advanced economies. Authors' empirical results confirm previous findings giving support to the inverted U-shaped relationship between income and manufacturing in employment. Results also show that global exchanges have the potential to affect sectoral patterns of employment. Sposi, Yi and Zhang (2024) present econometric evidence for 28 countries of two driving forces, sector productivity growth and trade integration, working together behind deindustrialization and found increasing industry polarization.

In contrast, in this paper, we take a complex systems perspective, in which the key in a deindustrialization process is the centrality of the manufacturing sectors in the entire structure of the economic system. This perspective emphasizes the emergence of aggregated outcomes coming from the intersectional interactions and feedback effects rather than defining causal relations. We center our investigation on the case of Mexico because the poor economic performance of Mexico has been attributed in part to a deindustrialization process. One of our objectives is to clarify if Mexico has experienced a deindustrialization and if this has had an effect on the structure of the economy. When one observes traditional signs of deindustrialization the result is not clear. From 2008 to 2018, we observe that the contribution of manufacturing on value added increased from 16 to 20 percent mainly driven by an increase in the participation of machinery, equipment, motors, electrical components, cars, and car parts. Despite this rise in manufacturing contributions, we should investigate further. Deindustrialization of the Mexican economy is highly relevant for many reasons including the fact that Mexico has been traditionally an exporter of manufacturing sectors such as machinery, equipment, motors, electrical components, cars, and car parts. Additionally, Mexico has been applying an export-driven growth model. Therefore, the research problem to solve is how can we obtain evidence of a deindustrialization process different from manufacturing share of value added and total production and what are the effects of this process on the structure of the economy.

Evidence regarding the deindustrialization of the Mexican economy has been documented for years. In González Arévalo (2017), authors describe low manufacturing growth rates, a decreasing manufacturing GDP participation that went from 19.7 in 2000 to 16.8 in 2015, a deficit in the trade balance of the manufacturing industry, and a low fixed capital formation. Moreover, the deindustrialization coefficient, measured as manufacturing imports as a share of manufacturing GDP, has increased giving evidence of a higher dependence of trade on supply inputs. Consequently, authors in González Arévalo (2017) highlight the fact that, from a Kaldorian perspective, a lowering manufacturing GDP share in total GDP is not as important as a share of total production and other factors. Salama (2020) mentions that high imports in manufacturing industries are a sign of deindustrialization because they limit the level of industrial tissue from transforming the manufacturing industries into a more complex one. Authors mention the absence of an industrial policy and the only apparent sophistication of manufacturing products that are exported as important factors for this situation. The majority of manufacturing products that are exported are only assembled in the country and value added generated in their production is also exported. Therefore, the Mexican economy shows low chain effects and a low degree of national integration worsened by the mentioned absence of an industrial policy (Salama, 2020).

Calderón-Villarreal and Hernández Biela (2016) document that the Mexican economy has not grown and exhibits high unemployment, low quality jobs, and low wages despite the fact that it has signed several free trade agreements and followed all recommendations from international organizations. According to them, sectoral changes and changes in the productive structure of the Mexican economy have taken the economy to a deindustrialization and towards a service economy. The absence of an industrial policy worsens the negative effects. Those authors point to the fact that the first signs of deindustrialization were observed since the 1980s but were mainly felt since the sign of North American Free Trade Agreement (NAFTA). As a result, manufacturing GDP share started to decrease (Calderón-Villarreal and Hernández Biela, 2016).

The documented performance of Mexico highlights the need for a structural analysis of the productive structure. We are interested in clarifying the nature of the changes that Mexico's economy has experienced. Therefore, in this paper we complement the existing literature by analyzing structural properties of the Mexican economy over a ten-year period. For such a task we combined input-output data with complex network analysis. We consider the economy as a complex system and model it as a network to emphasize the interactions between heterogeneous sectors. The organization of these interactions elucidates the configuration of the system. Changes in this organization may reflect a reconfiguration of the economy. Therefore, in this perspective a deindustrialization process would involve destruction, creation, or substitution of intersectional relations and therefore will result in a reconfiguration of the entire economy.

Input-output matrices offer a means to study the productive structure of a country by providing a photograph of the intersectional interactions at a given point in time. By comparing tables at different years, we can analyze whether the economy in question experienced changes in its structure. Input-output literature is vast and offers different tools to study the structure of intersectional relations. In this literature we find impact analysis where sectors with above average linkages are suited for selective promotion in a development strategy because they generate higher effects on the economy (Miller and Blair, 2009; McGilvray, 1976; Hirschman, 1958). Comparably, network analysis provides tools to analyze the structural properties of a system. Among the analyses we find in complex network there is the identification of most central nodes according to different centrality measures. In this paper, we compute three different centrality measures: Degree, strength, and authority and hub scores.

The input-output data we use to represent the economy as a network is the intermediate demands. Input-output tables for Mexico are published by the Instituto Nacional de Estadística y Geografía (INEGI). In particular, we use tables for the years 2008, 2013, and 2018. In the production network, the sectors are nodes and intersectional interactions are weighted directed edges connecting the nodes. These connections represent supply and demand of inputs. Following the construction of the networks, we apply complex network analysis to characterize the structural properties of each production network. To be able to compare the productive structure for different years we homologize the Mexican input-output tables at the class level so that we have the same number of nodes.

Most relevant results provide evidence that the Mexican economy has similar aggregated properties in the period of study. However, it experienced changes in structural properties related to the organization of sectors in the production system. In particular, intermediate demands were best described by the logistic distribution with changes in the estimated parameters. The increase in the estimated parameters of shape and scale are evidence of a flatter distribution. Interestingly, the number of intersectional relations increased since 2013. The density of the production networks increased from 2008 to 2013 and from 2013 to 2018. Measures of centrality such as degrees and strengths showed that sectors had more connections and slightly stronger ones. Nevertheless, the ranking of most central sectors changed. Some sectors improved ranking and others declined. This change in the organization of sectors provides evidence of a shift in economic activities from manufacturing towards oil-related and service activities. Therefore, evidence of complex network analysis for the Mexican economy shows a reconfiguration of the Mexican economy where manufacturing sectors are becoming less central in the production structure.

The remainder of the paper is organized as follows. The second section presents data and methods where we present how we use input-output data to construct productive networks. The third section presents results, section four discusses the relevance of results. In section five we conclude.

2. DATA AND METHODS

2.1. Data

We use input-output data that provide information regarding intersectional relations. In particular, these tables contain data about intermediate demands and final demands. We use input-output tables for the years 2008, 2013 and 2018. These tables were published by the INEGI in 2009, 2014 and 2019 respectively and are publicly available. The tables classified the economy at the Sistema de Clasificación Industrial de América del Norte (SCIAN) class level in 2008 into 814 sectors, in 2013 into 822, and in 2018 into 834 sectors.

Input-output data is organized according to the Input-Output Model first proposed by W. Leontief to study interdependencies between sectors. In the Input-Output Model total production is computed as a linear combination of the production of all sectors in the economic system plus an exogenous final demand as follows (Leontief, 1936 and 1949):

$$X = \mathrm{A}\mathbf{X} + \mathbf{F}$$

Where A is the direct coefficients squared matrix, **X** is the final production column vector and **F** is the final demand column vector. Intermediate demands represent the linear combination of the production of all sectors and are $Z = \mathrm{A}\mathbf{X}$. Therefore, in terms of intermediate demands, total sectoral production is:

$$X = \mathrm{Z}\mathbf{1} + \mathbf{F}$$

Where $z_{ij} \geq 0$ provides the flux of money paid by i to j registered when j supplied part of its production as input for i's production, and **1** is the sum vector, a vector of ones.

In order to be able to compare the structural properties of production networks at three points in time we need to homologize the number of sectors. In particular, there are cases where one sector in 2008 was split into several sectors in 2013 and 2018. In these cases, we summed values for these sectors to make them equivalent to the one found in 2008. This was performed as a row and column sum of the Z matrix corresponding to the sectors involved in the changes. For example, sector 111214: Watermelon and melon in 2008 was split into 111214: Melon and 111218: Watermelon in 2013 and 2018; in this case we summed values for sectors 111214 and 111218 in 2013 and 2018. After performing all changes required, all three input-output tables have 803 sectors. We summarize all the changes required to homologized matrices in Table A1 in the Appendix.

We are now able to construct production networks and compare their structure to analyze whether there was a reconfiguration in the Mexican economy. In the next section we describe how we construct production networks using information from the input-output tables and how we compute network measures.

2.2. Methods

The input-output tables are a natural source of data for constructing production networks. A network is a graph $G(V,E)$, $V = \{v_i, i = 1,\ldots,n\}$, where n = number of sectors, and $E = \{e_{ij}, i = 1,\ldots,n, \text{ and } j = 1,\ldots,n\}$, where $e_{ij} \geq 0$ are directed edges weighted by $z_{ij} > 0$, the intermediate demands. If $e_{ij} > 0$ then there exists a connection between sectors i and j. If $e_{ij} = 0$, then there is no connection between i and j. The E matrix is not symmetric, therefore $e_{ij} \neq e_{ji}$. Recall that these directed edges represent the flow of supply and demand of inputs, therefore sector i may supply an input to sector j but j may not supply an input to sector i. We allow e_{ij} for $i = j$, which accounts for self loops and the case when a sector is using its own product as input.

To analyze structural properties of production networks we compute the following. Measures: Number of total edges, number of edges of manufacturing sectors, density, and centrality measures that include in degree, out degree, in strength, out strength, and authority and hub scores. Density is a measure of connectivity and is computed as the number of edges divided by the number of edges that would exist if all nodes were connected (Newman, 2003 and 2010).

Regarding centrality measures, degrees count the number of direct adjacent links incoming and outgoing, therefore giving information about the number of suppliers and buyers of inputs and are computed as the column and row sum of the binary adjacency matrix where an element is equal to one if there exists a connection between two nodes and cero otherwise (Newman, 2003 and 2010). Strength is a measure of weighted degree where the centrality of a node considers the number and strength of the connections and is computed as the column and row sum of the weighted adjacency matrix (Newman, 2003 and 2010). A node may outrank another one in strength even if it does not outrank it in degree. Lastly, authority and hub scores are a generalization of eigenvector centrality for directed networks and are measures of mutually reinforcing centralities based on the fact that good authorities (nodes with the highest authority scores) point to good hubs (nodes with the highest hub scores) and good hubs are pointed by good authorities (Kleinberg, 1999; Newman, 2010). Each node has both an authority and a hub score. Scores are computed through an iterative algorithm, called the Hyperlink-Induced Topic Search (HITS) algorithm, until convergence using the iterative power method for computing the dominant eigenvector of $A^T A$ and AA^T, where A is the binary adjacency matrix; these matrices are symmetric positive semidefinite and non-negative (Langville and Meyer, 2005). We compare the most central sectors in the three years of study comparing the ranking obtained with the computation of all measures.

As part of the exploratory data analysis required to characterize the structural properties, we adopt a non-parametric approach that includes performing best fit analysis to the intermediate demands matrix and Spearman correlations. Best fit analysis identifies the random variable that best describes the behaviour of a collection of observed values. For the best fit test, we fitted the data to different distributions of continuous variables using maximum likelihood estimation and obtained estimators for shape, location and scale parameters for the distributions of different continuous random variables. Then, with the maximum likelihood estimators (MLEs), we performed the Kolmogorov-Smirnov (KS) goodness of fit test to obtain the distribution that best described the data for each MLE fit. The best approximation is the distribution with the smallest

D-statistic among all distributions. The KS test for goodness of fit performs a test of the distribution of an observed random variable against a given distribution under the null hypothesis that the two distributions are identical. We report D-statistics and p-values of the KS tests, and MLEs for each fit. When we identify the distribution that best described observables, this becomes a mathematical model that could be used to predict, but also could be used to compare and better understand the behaviors at different years. The Spearman correlation coefficient assesses monotonic relations and therefore, does not assume a linear relation between two sets of data. The Spearman correlation coefficient can take values between –1 and 1, where 0 means no correlation.

3. RESULTS

We first describe the characteristics of edges of nodes in production networks that represent the flow of the supply and demand of inputs, and report any changes. Then, we report structural properties of networks, and the exploratory data analysis, including the best fit analysis.

Most of the values of intermediate demands are zero or values close to zero with few values much higher. This characteristic results in a distribution with values concentrated around zero and a long tail to the right. This describes a highly skewed distribution.

From 2008 to 2018 the economy became more connected. The number of intersectional interactions increased by 18.7% from 2008 to 2013 and 5% from 2013 to 2018. Table 1 shows results for the density and entropy of the production network. We observe that the increase in the number of intersectoral relations was translated into an increase in network density of 22% and 5% respectively. Entropy related to intermediate demands increased from 2008 to 2013 from 11.329 to 11.740 but decreased to 11.69 on 2018 (Table 1). These changes show that the first half of the period the distribution of intermediate demands must have become flatter with more even observed frequencies. On the contrary, from 2013 to 2018 intermediate demands became slightly more diverse in frequencies. This is evidence of a change in intersectional relations. Due to the classification of sectors and the homologation, the number of sectors that belong to manufacturing industries remained the same for all three years at 285, that is, 35.5% of all sectors.

Table 2 presents results for the configuration of edges from 2008 to 2018. We observe that the number of edges between manufacturing sectors increased from 2008 to 2013 but considerably decreased from 2013 to 2018. As a percentage of the total of edges, we observe a drop in all the ten-year period. From 2013 to 2018 the decreased represented 19.64% less edges. This behaviour is the same for the number of edges of input buyers of nodes inside the manufacturing industry, but the decrease was less abrupt, representing 12.98% less edges in 2018 compared to 2013.

Comparably, the number of connections of nodes inside the manufacturing industries that supply inputs to other nodes outside the man-

Table 1. Density and entropy

Measure	2008	2013	2018
Density	0.0909	0.1109	0.1167
Entropy	11.329	11.740	11.692

Table 2. Edges

	2008	2013	2018
Number of edges	60,200	71,467	75,191
Number of nodes in manufacturing	285	285	285
Number of edges of nodes in manufacturing	20,016	21,771	17,496
Percentage of total edges	33.249	30.463	23.217
Number of edges of nodes that buy inputs from nodes in manufacturing	35,419	38,126	33,179
Percentage of total edges	58.836	53.348	44.028
Number of edges of nodes in manufacturing that supply inputs to other nodes outside the manufacturing industry	28,584	35,237	36,664
Percentage of total edges	47.48	49.31	48.65

ufacturing industry increased in all periods suggesting the creation of production chains of intermediary products. However, as a percentage of total connections in the network, this type of links only increased from 2008 to 2013, but decreased from 2013 to 2018. Nevertheless, if we observe the ten year period, the percentage increased more than one percentage from 47.48 to 48.65. This points to the fact that the role of the manufacturing industry as an input supplier has not been negatively affected. Consequently, connections for the supply of inputs have not been destroyed.

Next, we analyze how the organization of sectors has changed and whether these changes provide evidence of a reconfiguration of the economy obeying a deindustrialization process. When analyzing the structure and organization of sectors and intersectional relations, the number of connections is not the only factor that is important. One has to consider also the strength or weight of such connections and the global role of nodes in the network. Spearman correlations between centrality measures in the three years of study show that from 2008 and 2013 the relation between the rankings of sectors is around 0.6 giving evidence of statistical differences in the positions of sectors in all centrality measures. From 2013 to 2018 the Spearman correlation between centrality measures slightly increased for most measures showing a change in positions in the ranking of sectors from one year to the other, but displaying a closer ranking in 2018 compare to 2013 than the one observed in 2013 compared to 2008.

As part of the data exploratory analysis, we present results for a descriptive analysis of the centrality measures for the three years of study in Table 3. We observe that central tendency measures, in particular the mean and median, increased year by year for most measures excluding authority and hub scores. On the contrary, skewness decreased for all measures in the 10-year period. Remarkably, the distributions for in degree were the ones less skewed and, by the end of the period, the distribution was much less asymmetrical. We observe this behaviour in Figure 1. The rest of the centrality measures remained highly asymmetrical despite the decreased in skewness. This characteristic is also evident when we observe the differences between the mean and the median of centrality measures.

Table 3. Descriptive statistics of centrality measures for all years

Centrality	Mean	Standard deviation	0.25	0.50	0.75	Skew-ness	Kurtosis
In degree 2008	0.09	0.08	0.04	0.07	0.13	1.36	1.64
In degree 2013	0.11	0.08	0.05	0.09	0.15	1.14	0.91
In degree 2018	0.12	0.07	0.06	0.11	0.16	0.94	1.85
Out degree 2008	0.09	0.16	0.00	0.02	0.12	2.78	9.00
Out degree 2013	0.11	0.18	0.00	0.03	0.14	2.42	5.97
Out degree 2018	0.12	0.19	0.01	0.03	0.14	2.31	5.33
In strength 2008	11,157.08	39,597.02	496.00	1,888.00	7,102.50	10.15	134.62
In strength 2013	16,932.44	53,346.61	968.50	3,556.00	12,068.50	9.44	118.68
In strength 2018	27,024.38	83,796.51	1,684.00	5,441.50	20,283.50	8.35	89.61
Out strength 2008	11,157.08	47,729.15	62.00	1,190.00	6,560.00	11.10	147.11
Out strength 2013	16,932.44	70,284.05	175.50	1,959.00	10,442.00	11.28	150.97
Out strength 2018	27,024.38	98,238.45	661.25	4,170.50	18,375.00	10.32	135.64
Hub score 2008	0.00	0.02	0.00	0.00	0.00	22.16	518.39
Hub score 2013	0.00	0.02	0.00	0.00	0.00	19.87	404.46
Hub score 2018	0.00	0.01	0.00	0.00	0.00	16.70	313.26
Authority score 2008	0.00	0.02	0.00	0.00	0.00	25.60	688.33
Authority score 2013	0.00	0.02	0.00	0.00	0.00	25.91	705.38
Authority score 2018	0.00	0.01	0.00	0.00	0.00	17.08	330.53

Figure 1. Degrees

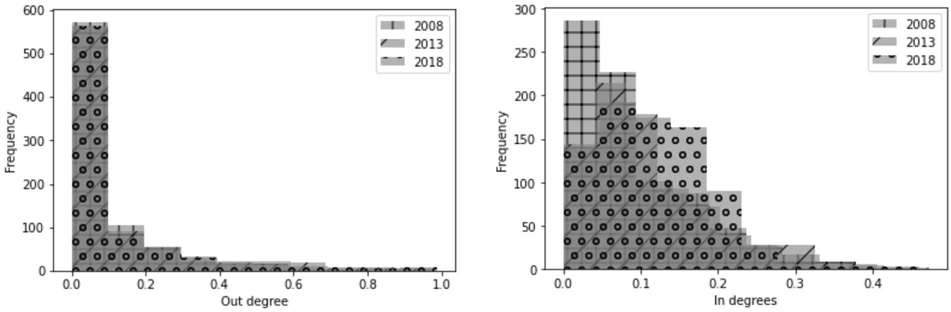
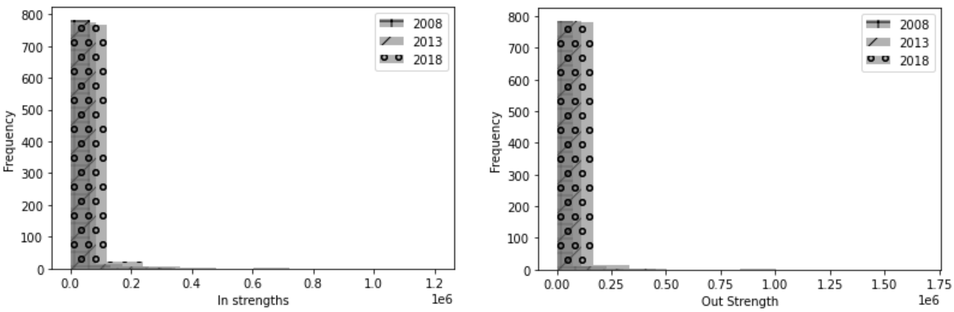


Figure 1 shows the frequency distributions for in degree and out degree where the horizontal axis displays normalized degrees. We observe a change in the distribution of in degree values. In 2018 we find less frequency of values close to zero and more frequency of values between 0.1 and 0.2. Therefore, the distribution has a short and thin tail where highest values are above 0.4 and have very low frequency. Despite this shape, in 2018, nodes have more incoming connections compared to 2008. The number of outgoing connections are more concentrated on low values ranging from 0 to 0.2 High values above 0.6 and close to one have very low frequencies. Therefore, the distribution has a long but thin tail. In 2008 most central sectors according to the number of incoming connections were trade, construction, and eight different manufacturing sectors. Figure 1 also shows that the frequency distribution of out-degree values remained practically unchanged in all periods. According to outgoing connections trade remains at the top, but other sectors appeared at the top of the ranking such as oil refining, generation, transmission and distribution of electric energy, telecommunications, local transportation of agricultural products, and banking.

Figure 2 shows the frequency distributions of strengths. We observe that strengths are much more concentrated on low values from 0 to 0.2. Both distributions are less disperse and diverse, and have a short and thin tail. In 2018 compared to 2008, the distribution became wider and we observe more values above 0.1. When considering the strength of incoming connections, we find oil refining in the first place and trade in the second place; in the following positions we find manufacturing of basic chemicals from natural gas and refined oil, construction of one-family

Figure 2. Strengths

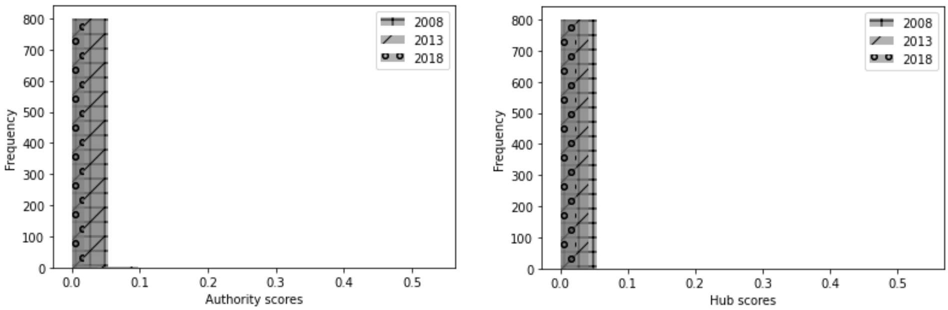


housing, manufacturing of motor vehicles and trucks, manufacturing of audio and video, generation, transmission and distribution of electric energy, local transportation of agricultural products, slaughter of cattle fowl and other eatable animals, and construction of commercial and services buildings. Out strength ranks at the top trade, oil refining, oil extraction, manufacturing of basic chemicals from natural gas and refined oil, personal supply, generation, transmission and distribution of electric energy, manufacturing of electric components, real-state without intermediaries of offices and commercial places, iron and steel industry and accounting and counseling.

In figure 3 we show frequency distributions of authority and hub scores. We observe highly concentrated values between 0 and 0.1. Additionally, we observe a very thin and short tail. When we compare 2018 to 2008, we find that values are even more concentrated around zero (bar with circles to the left in Figure 3). This is evidence of a decrease in scores. In particular, the ranking of hub and authority scores report similar sectors in the top ten but in different positions. Additionally, sectors that were not at the top ten appeared in the highest positions such as: Corporate, manufacturing of metallic pieces, passenger land transport, and air transport.

From 2008 to 2013 we observe a decrease in the number of manufacturing sectors ranked as the most central. In 2008, there were 12 manufacturing ranked as most central according to centrality measures: Other parts of motor vehicles; other measurements, control, medical and sailing instruments; electric components, electric and electronic equipment and parts for motor vehicles; equipment and apparel for the

Figure 3. Authority and hub scores



distribution of electric energy; audio and video equipment; other plastic products without reinforcement; other metallic products; oil refining; basic chemicals from natural gas and refined oil; cars and trucks; metallic pieces for machinery and equipment; and other basic organic chemicals. In 2013, eleven manufacturing sectors were at the top ten according to all measures: Other measurement, control, electric medical equipment instruments; other motor vehicles parts; distribution equipment and apparel; electronic components; oil refining; cars and trucks; audio and video equipment; computer and peripheral equipment; electronic components; basic chemicals from natural gas and oil; and other chemical products. Finally, in 2018 only seven sectors appeared at the top ten of authority and hub scores: Oil refining; cars and trucks; computer and peripheral equipment; electrical components manufacturing; basic chemicals from natural gas and oil; audio and video equipment; and electric and electronic equipment and parts for motor vehicles. At the top ten of the other measures we only find oil refining and computer and peripheral equipment.

These results show a clear change in the ranking of manufacturing sectors where oil refining, oil extraction, and manufacturing of basic chemicals from natural gas and refined oil climbed in positions while the rest of the manufacturing sectors descended. On the other hand, retail and wholesale trade maintain their position, and land transport gained centrality. This behavior was more pronounced in 2018, were only manufacturing of basic chemicals from natural gas and refined oil, manufacturing of electronic components and manufacturing of computers and peripheral equipment appeared as most central according to some measures. Comparably, in 2008, eight manufacturing sectors appeared in the top ten; an important reduction.

Table 4 presents results for the best fit analysis. We observe that in the three years of study the distribution of intermediate demands was best described by a logistic distribution. The logistic distribution is a function of a continuous random variable that shows wider tails than the normal distribution and therefore provides a better model for the appearance of extreme values. Estimated parameters (MLEs) for mean (location) and variance (scale) of the best fit of the intermediate demands show a change in the shape of the distribution. We observe both estimated parameters increased considerably their values in the time period. The increased variance transformed the distribution into a wider one. This result provides evidence of a decrease in the concentration of values. These findings suggest a reconfiguration of the economic system.

The results, together with the change in the hierarchical organization of sectors and the change in the configuration of edges outside and inside manufacturing activities provide evidence of a deindustrialization process in Mexico from 2008-2018.

4. DISCUSSION

From 2008 to 2013 the density of the Mexican production network increased as a result of an increase in input-output connections. However, the configuration of these connections changed. There were new input-output connections outside the manufacturing sectors but inside the manufacturing industry intersectional connections were destroyed. Similarly, from 2013 to 2018 input-output connections between the

Table 4. Best fit analysis

Year	Best fit distribution	Probability distribution	(D-statistic, p-value)	MLEs
2008	Logistic		(0.481, 0.0)	(1.046, 13.607)
2013	Logistic	$f(x) = \frac{e^{-x}}{(1+e^{-x})^2}$	(0.479, 0.0)	(1.748, 20.600)
2018	Logistic		(0.480, 0.0)	(2.590, 32.868)

manufacturing sectors were destroyed and fewer connections were created outside compared to the previous period.

Results of the creation and destruction of connections involving sectors in the manufacturing sectors provide evidence that these sectors as input suppliers were more affected in terms of the strength rather than the number of these connections.

Spearman correlations show differences in the ranking of sectors according to the different centrality measures. The decrease observed in the ranking of manufacturing activities in the most central nodes of the production network according to the different centrality measures provides evidence of a deindustrialization of the Mexican economy and a reconfiguration towards an oil-related and services activities economy.

The fact that the Logistic distribution appears in all the three years of study suggests that the reconfiguration of sectors did not mean a complete change in the structure of the production network. We interpreted this reconfiguration as a reorganization in the hierarchy of sectors but not as a structural change.

Data exploratory analysis and the best fit tests show a more disperse intermediate demands distribution, which implies less concentration around the mean value. Together with previous results regarding degrees, we find more connections but weaker ones which may turn the Mexican economy into a more vulnerable system when facing some types of perturbations in highly central sectors, especially good hubs and good authorities.

If we had relied uniquely on the share of manufacturing sectors in value added we could have concluded that the Mexican economy has been experiencing an industrialization process where the manufacturing sectors increased their contribution in total production and value added. However, this is not the case. The economy underwent a deindustrialization process that resulted in a reconfiguration of the structure. The relevance of manufacturing industries decreased in the productive structure. This was in part a result of a decrease in connections from manufacturing and between manufacturing sectors.

5. CONCLUSIONS

The Mexican economy experienced a deindustrialization process where manufacturing sectors became less central. This led to a reconfiguration in the production structure. Oil-related sectors such as extraction and transformation such as petrochemical, trade, service, together with public administration activities climbed positions to become more important.

This reconfiguration was reached without a big drop in the number of total connections but represented a decrease in the number of connections from and between manufacturing sectors and their strengths.

Mexico has failed to integrate the manufacturing sectors with the rest of the economic system due to the absence of an industrial policy that, beyond targeting sectors for selective promotion, develops production chains that generate value added for Mexico. ◄

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APPENDIX

Table A1. Homologation of input-output tables 2008, 2013, and 2018

2008	2013	2018
111214	111214,111218	111214,111218
111410	111410	111411, 111412, 111413, 111414, 111415, 111416, 111419
112211	112211, 112212	112211, 112212
212291	212291, 212299	212291, 212292, 212299
221110	221110	221111
222111	222111	221210
222210	222111	221312
311320, 311330	311350	311350
311812	311812	311812, 311813
333210	333241	333241
333220	333242	333242
333291	333243	333243
333292	333244	333244
333293	333245	333245
333294	333246	333246
333299	333249	333249
431110	431110, 461110	431110, 461110
485114	485114	485114, 485115
492110	492110, 492210	492110, 492210
512210, 512220	512210, 512220	512250
517111, 517112	517110	517311
517210	517210	517312
522390, 522410, 522420, 522430	522390	522390
522452	522352, 522460	522352, 522460

Table A1. Homologation of input-output tables 2008, 2013, and 2018 (concluded)

2008	2013	2018
531115	531115, 531116	531115, 531116
532220	532281	532281
532230	532230	Disappeared
532291	532282	532282
532292, 532299	532299	532289
562112	562121, 562211, 562221, 562911, 562921, 562998	562121, 562211, 562221, 562911, 562921, 562998
621114	621114, 621115	621114, 621115
-	712190	712190
721312, 722110, 722211, 722212, 722219	721312	721312
722412	722412, 722511, 722512, 722513, 722514, 722515, 722516, 722517, 722518, 722519	722412, 722511, 722512, 722513, 722514, 722515, 722516, 722517, 722518, 722519
	811123	811123
812320	812321	812321
932110	Disappeared	Disappeared