Network features in shaping sectors' responses to the Spillover effects of Covid -19 shocks

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Abstract

As inter-sectoral linkages are being increasingly organized in complex networks, It has become inconceivable to study sectors' responses to exogenous shocks without considering the nature of these invisible but real linkages Leontief (1941). However, although important, this research field remains poorly analyzed in both the theoretical and empirical literature. In this paper, we aim to investigate how sectors' network centrality and local density measures impact their responsiveness to sectoral shocks propagating through input-output linkages. Using Covid-19 shocks and complex network analysis, we find that sectors' various centrality and local density measures are correlated with the spillover effects of the supply and demand shocks. More specifically, we find key consumer sectors to bear higher indirect supply shocks, while major supplier sectors to be more vulnerable to the cascade effects of demand shocks. Furthermore, the correlation between sectors' sub-network characteristics with the indirect shocks has revealed the possibility of the simultaneous occurrence of a mitigation effect along with the contagion effect. Finally, We conclude by stating that, in a network theory framework, the sectoral impact of an exogenous shock not only depends the sector's relative position in the network but also on the nature of the shock itself.

Keywords: Production networks, Graph theory, Spillover effects, Input-Output, COVID-19 shocks.

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1 Introduction

With production structures being organized in an increasingly interconnected and complex manner, the response of economic sectors to crises of any kind (pandemics, wars, financial crisis, natural disasters, etc.) no longer depends only on sector's own shock, but also on shocks affecting all the other sectors propagating through input-output linkages. Indeed, by propagating shocks from one sector to another, these intersectoral linkages could lead to indirect effects that could be significantly larger than the direct effects (Acemoglu et al., 2016),translating them, eventually, and through the presence of key sectors, into aggregate fluctuations (Acemoglu et al., 2012, 2013; Carvalho, 2014; Carvalho and Tahbaz-Salehi, 2019).

Therefore, estimating the sectoral impact of exogenous shocks without taking into consideration these interconnections could lead to biased results and an underestimated economic impact.

Nevertheless, in the literature on production networks, the focus has been mainly on the study of the macroeconomic implications of the role and structural properties of these interconnections(density, degree strength, the presence of key sectors) yet, although very important, their sectoral effects have been overlooked in their analysis.

In this context, a recent study by Olabisi (2020) addresses this question by analyzing the relationship between sector's volatility and their corresponding position with respect to the final demand. Using a demand shock model Olabisi (2020), shows that sectors that are positioned upstream (far from final consumers) in the U.S production network are the most volatile in terms of their nominal output and exports.

However, this study does not consider the supply shocks along with demand shocks, differentiate between direct and indirect shocks, and more importantly does not take into account other structural properties of production networks that could play a major role in shaping sector's outcome and not only aggregate aggregate output as emphasized in the recent literature.

In this research paper, we aim to fill this gap in the literature by analysing, using the Covid-19 supply and demand shocks [1], the way in which the production network structure impacts sectors' output. More specifically, and drawing on the network theory, we investigate whether there is a relationship between the position of a sector within the production network and the indirect effects it bears through it?

To answer this question, we draw on the seminal work of Acemoglu et al. (2016) which has the merit of being directly mapped into data. In fact, building on the static multisector framework of Long Jr and Plosser (1983), Acemoglu et al. (2016), demonstrated theoretically and empirically that the output of each sector of the economy depends directly on its own shock and indirectly on the weighted shocks affecting all the other sectors with weights being the elements of the inverse of the Leontief matrix.

Thus, based on the model of Acemoglu et al. (2016) we compute the indirect effects of the covid-19 crisis for each sector using survey data on supply and demand shocks during the first wave of the pandemic, as well as the Tunisian 2018 input-output table. Results show that the indirect effects are very important and, for certain sectors, outweigh the direct shocks as highlighted by

[1]Our choice of the covid-19 crisis as our shock variable to the economy can be justified by several considerations. First, it is the most recent and most severe crisis to hit the world economy in more than a century; second, it affected the economic sectors in a heterogeneous way; it is simultaneously a supply and a demand shock and finally, its specificities make input-output models the most appropriate for the analysis of its economic impact.

the literature, on both the supply and demand sides. However these network effects are not homogeneous across sectors even when applying the same direct shock to all of them.

In order to investigate the potential sources of this heterogeneity we derived, in the second part of the paper the main structural properties of the Tunisian production network by computing different centrality and local density measures. Moreover, to study how important sectors in demand chains were hit by shocks propagating through intersectoral linkages, we constructed the second order indegree measure by taking the opposite of the second order outdegree equation developed by(Acemoglu et al., 2016). The high positive correlation between the second- and first-order indegrees testifies to some extent to the reliability of our measure (Oldham et al., 2019).

We finally conducted a pairwise correlation analysis to our variables. Our main results show that sectors with important first and second order centrality measures, from a demand side perspective, were more hit by the indirect supply shocks, whereas, major input suppliers were more exposed to the spillover effects of exogenous demand shocks. This findings converge with Acemoglu et al. (2016) theoretical and empirical statements, that supply shocks propagate mainly downstream, i.e. from suppliers to customers, while demand shocks transmit upstream. However, this finding highlight the importance of considering demand chains when estimating the impact of shocks transmitting through input-output linkages and not only key input suppliers as we can find in the recent literature. Second, we add to the literature (Olabisi, 2020) (Devulder and Lisack, 2020) () by stating that sectoral exposure to the ripple effects of independent shocks, is determined not only by a sector's relative position in the network, but also, by the nature of the shock itself.

Furthermore, by analysing sectors' local density measures we found evidence of a mitigation effect along with the contagion effect. A sector located in dense sub-networks could be, depending on the shock nature, more resilient and/or vulnerable to indirect shocks. In that, we join Joya and Rougier (2019) who argue that the structural properties of the production network can act simultaneously as conductors and inhibitors of shocks originating elsewhere in the economy.

Therefore, to disentangle the sectoral impact of a shock that propagates through complex networks, we must take advantage of the burgeoning field of network theory and undertake more comprehensive studies.

Our paper constitutes a first attempt to investigate the presence of a relationship between sectors' network properties and the degree of their exposure to indirect shocks. We are aware that a more rigorous econometric analysis that takes into account other sectors characteristics as well as other determinant variables is warranted.

The rest of the paper is structured as follows, section **??** literature review section **??** methodology and data section**??**Results and discussion section**??**the conclusion.

2 Literature Review

In light of the strengthening of interconnections among the various economic agents both at the national and international levels, it has become inconceivable to study the various economic dynamics and outcomes while not considering these linkages and their respective properties.

In this context, the literature on network science has shown that networks displaying distinct structures can result into important differences in the behaviors of agents in the network Jackson

(2014); **?**(Jackson, 2014; Newman M.,2010) Barabási AL.,2016). Though accounting not only for the existence of these networks but also for their patterns and components' characteristics, in economic research, can provide important insights and help academics to model and understand observable but poorly understood economic outcomes.

In this respect, several developments have been made, since the seminal work of Leontief (1936, 1941), in the analysis of the role of economic networks, at the firm, sector and financial level, in explaining economic results. Using different network approaches, these studies aimed broadly at evaluating the ripple effects of exogenous shocks (Acemoglu at al.,) and/or in explaining the network origins of aggregate fluctuations.

Using the U.S. input-output table, and two different supply and demand shocks, Acemoglu et al. (2016), demonstrated that supply shocks propagate downstream the network , while demand shocks spread only upstream, and that these spillover effects outpace the direct shocks to sectors. Similar results were obtained by Acemoglu, Autor, Dorn, Hanson, and Price (2015) in assessing the impact of the penetration of Chinese trade on the U.S. labor market by focusing on 10- or 20-year effects. They further documented that these inter-sectoral linkages not only propagated trade shocks but also amplified them by doubling their effects in manufacturing sectors.

Indeed, the assumption of the amplification of sectoral or firm-specific shocks through production networks came to contradict the diversification argument which states that idiosyncratic shocks wash out as the number of firms or sectors increases (Lucas,1977).

In fact, several research papers have demonstrated that an asymmetric structure of the supply network, translating the existence of a small number of key sectors acting as major suppliers of inputs to the economy, enables the transformation of disaggregated shocks into macroeconomic fluctuations (Acemoglu et al.,. 2010; Carvalho 2014; Acemoglu et al., 2012). These hub-like sectors serve as a channel for the transmission of disturbances originating elsewhere in the economy and their aggregation [2] (Acemoglu et al.2012, 2016b; Baqaee, 2016; Carvalho, 2019; Atalay, 2017; Baqaee and Farhi, 2018).

Using graph theory techniques, another strand of the literature, investigated the extent to which specific patterns of connectivity of a node (firms, sectors or financial institutions) determine the way they spread shocks through networks.

Joya and Rougier (2019), by computing different centrality and local density measures, show that exogenous demand shocks to central sectors entail a contagion effect that leads to aggregate volatility while shocks to sectors with high local density scores, positioned in dense sub-networks, tend rather to average out due to a substitution effect.

Financial networks have also retained academics' attentions specifically in the aftermath of the 2007-2008 global financial crisis which has triggered a series of studies investigating the extent to which the financial network structure and design can shape financial contagion pattern. A seminal work by Elliott et al., (2014), identify two financial network properties, the degree of diversification and integration of financial organizations, that have a defining and different role in cascading failures and defaults through the network. [3]

[2] This finding is of major importance, as it has allowed economists to recognize the network structural properties as a possible source of aggregate fluctuations, which was previously explained, conventionally, as being the result of aggregate shocks (Carvalho, 2014)

[3] Not to mention that these statements were the key argument of the U.S. governments bailouts of several leading institutions such as AIG and General Motors (Acemoglu et al., 2012; Elliott et al., 2014

The role of production networks in translating individual shocks into macroeconomic fluctuations has also been made evident through the large number of papers assessing the economic impact of crisis such as natural disasters and pandemics.

In assessing the impact of the 2011 Japan Earthquake, Carvalho et al., (2016) have demonstrated that input-output linkages, at the firm level, played a non trivial role in the propagation (directly and indirectly) and amplification of idiosyncratic shocks to devastated firms, accounting for a 1.2 percentage point contraction of the Japanese gross output in the year following the earthquake.

Similarly, during the recent Covid-19 pandemic a significant number of papers have used network-based models to analyze its economic effects. Indeed, affecting simultaneously the demand and supply side of the economy, and heterogeneously the different sectors, this crisis made input-output models the most adequate for the assessment of its economic repercussions (del Rio-Chanona et al.,2020).

From complex models , general equilibrium models Baqaee and Farhi(2020), Bonadio et al. (2020), agent-based model, Inoue and Todo (2020) , to more simpler modeling techniques, traditionnal input-output models Pichler and Farmer (2021), these studies have demonstrated that the adverse effects of the social distancing measures were substantially amplified by the feedback effects in production networks.

On the other hand, using general equilibrium framework based on a standard model of production networks, Barrot et al., (2020) show that sectors that were positioned upstream within the production network faced the highest decrease in their value added.

This finding highlights another important implication of network structure which relates to the question on how sector's network position and properties impact their responses to shocks propagating through input-output linkages.

In fact, while there exist a significant body of the literature, both theoretically and empirically, that analysis the macroeconomic implications of production network's characteristics, their microeconomic or sectoral effects have been only rarely studied.

By sectoral effects We suggest that sector's network characteristics not only determine their role as propagator and amplifiers of independent shocks but also the way in which they respond to these shocks. Indeed, graph theory argues that the network properties of a node determine not only its ability to influence but also to be influenced through its interconnection properties (Oldham et al., 2019).

A study by Olabisi (2019), in investigating the origins of sector's output volatility, demonstrates that sectors that are positioned upstream within the production network, far from final consumers, by accumulating shocks from all downstream sectors in the network, face a higher level of nominal output volatility in response to exogenous demand shocks than more customer-facing sectors. He further shows that the upstreamness measure account for almost 15 per cent of sectors' growth rate fluctuations.

Exploiting rather graph theory techniques, Ahern (2013), construct a complete economic network with almost 500 disaggregated sectors over a 20 year time span and demonstrate that the most central sectors in the network, captured by the eigenvector centrality measure, received the higher stock returns as being the most exposed to sectoral shocks.

Undoubtedly, these papers have provided first evidence that sector's relative position and properties within production networks is an important determinant of its exposure to exogenous shocks and performance.

However, they do not take into account the impact of supply shocks along with demand shocks as Acemoglu et al., (2016) have evidenced that these two shocks do not follow a common propagation pattern. Supply shocks transmit only downstream, from supplier sectors to customer sectors, while demand shocks propagate only upstream. Therefore, we expect that with different network properties and positions sectors would not respond the same way to supply shocks as to demand shocks.

In this respect, our paper contributes to this literature by investigating the sectoral impact of the propagation of the Covid-19 supply and demand shocks through the Tunisian input-output network.

Furthermore, recent literature makes no distinction between direct and indirect effects when assessing sector's responsiveness to exogenous shocks. Acemoglu et al., (2016) demonstrated that it is the indirect component of the total effect that depends on the Leontief inverse matrix and therefore on the properties of sectors interconnections. Though we believe that considering network effects rather than total sector volatility would allow us to better identify and specify the relationship between sectors' network properties and their exposure to shocks originating elsewhere in the economy.

On the other hand, in identifying key sectors in the economy, Olabisi (2019) and Ahern (2013) do not make use of different graph theory and network science techniques that enable a more accurate characterization of sectors within production networks.

Olabisi (2019), identify upstream sectors by measuring the number of production stages between sector's inputs and final consumers. Ahern (2013) uses, instead the eigenvector centrality to measure sector's centrality in the economy. This method has the disadvantage of not penalizing distant connections (Newmann, 2010).

In fact, the complex nature of production chains requires a better characterization of these intersectoral linkages to better explain their implications on economic behaviors.

In our paper, we contribute to this literature, by exploiting complex graph theory techniques. We first compute various centrality metrics that account not only for important sectors from a supply side perspective but also from a demand side perspective. Second we determine local density measures that describe sector's relative position within sub networks.

Finally to the best of our knowledge our paper is the first that addresses this question for a developing country, this is important as production networks' structures in developed economies differ from production networks in developing ones.

3 Methodology and Data

3.1 Methodology

In order to investigate the role of the Tunisian production network properties in shaping sector's output following an exogenous shock, which in the context of this paper corresponds to the covid-19 supply and demand shocks, we first determine the network effects of these shocks, and then derive the network measures, on which we finally perform a correlation analysis.

3.1.1 Network effects of the Covid-19 supply and demand shocks

To study the indirect impact of domestic supply and demand shocks across economic sectors we rely on the work of (Acemoglu et al., 2016). In their seminal work, they developed a theoretical framework that has the merit of being easily and directly mapped into data.

Based on the model of (Long Jr and Plosser, 1983) and (Acemoglu et al., 2012), Acemoglu et al. (2016) assess the theoretical implications of intersectoral linkages. Starting from a perfectly competitive static economy, with a Cobb Douglas production and a household utility functions , they show that in competitive equilibrium, profit maximization implies the following relationship:

$$a_{ij} = \frac{p_j x_{ij}}{p_i y_i} \tag{1}$$

where a_{ij} is defined as an element of the matrix A, and measures sales from sector j to sector i normalized by sales of sector i. Using this matrix, which reflects input-output shares of the corresponding input-output table, Acemoglu et al. (2016) demonstrate that the output of each sector i in the economy depends directly on its own shock and indirectly on shocks hitting all the other sectors. Furthermore, they show that with of a Cobb-Douglas preferences and technologies, supply side shocks propagate only from input supplying sectors to customer sectors (downstream propagation) and demand shocks propagate only from customer sectors to input supplying sectors (upstream propagation). Thus, Acemoglu et al. (2016) define the impact of a supply shock on sector's i output by the following equation:

$$dlny_i = ds_i + \sum_{j=1} (l_{ij} - 1_{i=j}) \times ds_j \tag{2}$$

Where ds_i is the own direct shock of sector i, and the right hand side of the equation describes the indirect (network) effect of supply side shocks i.e., the impact of supply shocks from sectors j (j=1.....n) on the output of sector i running through indirect linkages. These indirect linkages are represented by the Leontief inverse (L) of the input-output share matrix (A) and are defined as follows:

$$L = (I - A)^{-1} \tag{3}$$

With $l_i j$ is the ij-th element of L and I an identity matrix This matrix represents the fundamental element in the analysis of the propagation and evaluation of the indirect effects of microeconomic (sectoral) shocks. In the case of a supply side shock the Leontief inverse matrix translates downstream linkages, as shocks propagate only from supplying sectors to customer sectors. For the propagation of demand side shocks, Acemoglu et al. (2016) show that the response of a sector to a demand shock is expressed by the following equation:

$$dlny_i = ds_i \times \frac{1}{y_i p_i} + \sum_{j=1} (l_{ij} - 1_{i=j}) \times ds_j \times \frac{1}{y_j p_j} \tag{4}$$

Where the ds_i is the own direct shock and the right hand side outline the indirect impact of demand shocks to j sectors. $l_j i$ the ij-th element of the Leontief inverse (L) of B matrix. 1 is the indicator function for j=i.

$$L = (I - B)^{-1} \tag{5}$$

B is the input-output share matrix in which we define $b_i j$ as a typical entry, where $b_i j$ represents sales from sector j to sector i normalized by sales of sector j ($y_j p_j$).

$$b_{ij} = \frac{p_j x_{ij}}{p_j y_j} \tag{6}$$

As such, the Leontief inverse of the B matrix ensures, uniquely, the transmission of demand side shocks from the customer sectors (downstream sectors) to the input supplying sectors (upstream sectors), we thus refer to these indirect linkages as upstream linkages.

Therefore, in order to quantify sectoral effects of supply and demand covid-19 related shocks, we mimic exactly equations (2) and (4), and by computing, beforehand, downstream and upstream linkages. The downstream and upstream effects, thus, correspond to the weighted shocks to all the other sectors with weights being the elements of the Leontief inverse matrices, (L) for the downstream effect and (B) for the upstream effect.

To compute downstream and upstream linkages, we use the 2018 Tunisian input-output table and construct the corresponding Leontief inverse matrices.

The presence of the Leontief inverse matrices in equations (2) and (4) shows that a sector's response to shocks depends on the characteristics of the intersectoral production network and therefore on the degree of sectors' interconnections with respect to their direct and indirect suppliers and customers.

3.1.2 Production networks structure and sector's output

The theoretical framework developed by Acemoglu and al. (2016), shows that sector's output depends on a well-defined network object, captured by the presence of the Leontief inverse matrices.

In this section our objective is to derive, by adopting a network approach, the main features of this network and conduct a correlation analysis in order to identify network properties that best explain the heterogeneity of indirect effects across sectors.

We first perform a descriptive analysis of the Tunisian production network by computing basic network statistics such as density, distance and diameter which provide an insight into the propagation pattern of shocks across sectors. We then conduct an in-depth analysis of sector's network features to investigate how sectors' upstream and downstream structure of interconnections impacts their respective responses to exogenous shocks. In this section we dig deeper into the analysis of the properties of the Tunisian Production Network by computing sectors' first and second order centrality measures and local density measures.

The density of network measure, defined by the proportion of linkages, edges in network parlance,that exist between sectors (nodes) relative to the number of possible connections, translates the extent to which sectors are interconnected within the production network. The more interconnected the production network is, the faster local shocks spread from one sector to another(author) Diameter and distance

3.1.3 First and Second order centrality Measures

The in(out)degree of a well-defined sector refers to the sum of the incoming (outgoing) linkages and correspond to the unweighted version of the input-output matrix, i.e. the adjacency matrix.

To construct this matrix, we follow Carvalho (2014) and assign 1 to an input transaction when the value of the traded input is greater than 1 per cent of the total input requirement of the sector in question and 0 otherwise.

The in(out)strengths, on the other hand, constitute the weighted version of the in(out)degrees and are calculated directly from the input-output matrix as follows:

$$d_{out} = \sum_{i=1}^{n} Z_{ji} \tag{7}$$

$$d_{ind} = \sum_{i=1}^{n} Z_{ij} \tag{8}$$

Equation 7 represents the weighted outdegree of sector i, which is simply the sum of the output of sector i that is consumed directly by the entire economy.

Similarly, Equation 8 expresses sector's weighted indegrees, which we refer to in the rest of the paper as the indegrees, that is the total sum of inputs provided by sector j and used by the rest of the economy.

However, while they only take into consideration direct upstream and downstream linkages,these first-order measures provide only partial information about the structure of intersectoral linkages (Acemoglu and al., 2012) and sector's relative positions within the production networks.

Therefore, in order to assess the importance of sectors as direct and indirect input suppliers, we need to dig deeper into our network analysis compute second order centrality measures.

In fact, Acemoglu et al, (2016) have demonstrated that second order measures of the weighted outdegrees are very important in the analysis of the propagation and amplification of sectoral shocks. They have shown that in the presence of an asymmetric structure between sectors in their role as direct and indirect suppliers of inputs to the rest of the economy, microeconomic shocks could translate into aggregate fluctuations. In this paper we are rather concerned by the sectoral implications of such a structure. In other terms, we question whether a sector's importance as a direct and indirect supplier (consumer) of inputs or its position within the production network has a defining role in shaping its response to sectoral shocks propagating through input-output linkages.

We thus adopt the definition of second-order outdegree put forward by Acemoglu and al. (2012), which states that the second-order outdegree of a sector i expresses the weighted sum of the outdegrees of the sectors that use the product of sector i as input with the weights given by their respective input shares.

$$d_{2out} = \sum_{i=1}^{n} outd_j^n Z_{ji} \tag{9}$$

However, in the literature on the importance of production networks as a mechanism for the propagation and amplification of microeconomic or sectoral shocks, the role of sectors as direct and indirect consumers of inputs has not been considered.

Indeed, since the focus in these studies was rather on the analysis of the macroeconomic implications of intersectoral connections, emphasis was instead placed on the study of sector's outdegrees, which by displaying an asymmetric distribution, allow for the transformation of sectoral shocks into aggregate fluctuations. Nonetheless, the main objective of this paper is to investigate how sector's network properties impact their corresponding response to sectoral shocks, we think that it is of a great importance to study not only their position as direct and indirect input suppliers but also as direct and indirect input consumers.

Thus, based on equation (8) and analogously to equation (9), we propose a measure of sector's second order indegrees described as follows:

$$d_{2in} = \sum_{i=1}^{n} ind_j^n Z_{ij} \tag{10}$$

where the term ind_j^n expresses the weighted sum of the indegrees of the sectors supplying inputs to sector i with the weights given by their respective output shares.

A high score reflects an important position of a sector as a direct and indirect consumer of inputs of the rest of the economy.

In the empirical literature on production networks, this upstream relationship (the relationship of a sector with its direct and indirect suppliers) is referred to as sector's input demand chain (Miller and Temurshoev, 2015), which is only rarely analyzed, in comparison with the input supply chain.

These second-order in(out)degrees, by linking sectors to their direct and indirect suppliers (consumers) of inputs, enable us to measure the extent to which sectors are exposed to indirect demand (supply) shocks.

In fact, from an intuitive perspective, we can expect that sector's with high second order outdegrees to be more vulnerable to indirect demand shocks while sector's with high levels of second order indegrees more likely to be subject to more important indirect supply shocks.

However, to investigate more accurately the relationship between a sector's position within a production network and its responsiveness to indirect shocks, we need to consider alternative network measures put forward by the social network science and the field of graph theory and adopted by the economic literature.

These network measures allow to identify key nodes within a network according to their position and degree of connectedness to other sectors.

Literature on production networks and the transmission of shocks through input-output linkages has adopted these measures not only to identify the propagation pattern of sector-specific shocks and their eventual amplification (Acemoglu and al., 2010 2013 2016; Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi; 2012, Carvalho, 2014; Carvalho and Salehi 2019), but also to investigate how network structure affects sector's responses to exogenous shocks (Ahern, 2013;).

The most widely used and well-known centrality measure developed in the literature on social and network theories is the eigenvector centrality (Carvalho, 2014; Giammetti, 2020). According to this "influence measure", a sector is considered as central if it is connected to sectors that have central position within the network of intersectoral linkages.

$$eigencentrality(x_i) = \frac{1}{\lambda}\sum_j W_{ij}x_j \tag{11}$$

Where:

x_i is the centrality of sector i,
x_j is the centrality of sector j,
W_{ij} represents the input-output linkages between sectors i and j,
λ is the largest eigenvalue of the adjacency matrix W, reflecting the importance of each sector within the broader network.

However, this measure, by not controlling for inter-node distance, may overestimate the ranking of a peripheral sector within the production network, even if that sector is only weakly connected to a key sector (Cerina et al., 2015; Giammetti 2020).

Indeed, as this measures quantifies the capacity of a sector to influence or be influenced by another sector following an exogenous shock, omitting the distance could lead to an overestimation of the network effect of this shock as distant connections result in a decrease of their transmission (Cerina et al., 2015 ; Giammetti, 2020).

Therefore, to address this problem, the input-output and network literature have, rather, adopted other variants of influence measures (Carvalho, 2014; Acemoglu, 2012; Cerina,2015) that penalize distance between sectors, notably the Katz Bonacich centrality measure adopted by the social network literature (Katz, 1953; Bonacich, 1987) and the Google's Page Rank Algorithm (Brin Page, 1998) from the computer science field. These network-based statistics are defined as follows:

$$KBC_i = \frac{1-\alpha}{n}(I - \lambda W')^{-1} \tag{12}$$

$$PR_i = (1-d) + d\sum_{j\in B(i)} \frac{PR(j)}{K_j^{out}} w_{(i,j)} \tag{13}$$

It is worth mentioning that the Bonacich centrality measure corresponds to the "influence vector" obtained in the expression of the aggregate equilibrium output by Acemoglu and al.,(2012) and Carvalho (2014), who demonstrate that the macroeconomic volatility of the economy depends on the network properties of the underlying input-output structure.

On the other hand, we consider the Page Rank centrality metric which was first developed to rank web pages in Google search through hypertextual information and was later used to rank nodes in different network types. According to this measure, a node is deemed to be central if it is connected to other nodes with important PageRank scores and low levels of outdegrees, and admit a high number of incoming links. Hence we would expect sectors with important PageRanks to be more exposed to indirect supply shocks.

Another relevant centrality measure, adopted by the input-output literature, is the Random Walk centrality developed by Blochl et al.,(2011), as Borgatti (2005) has shown that the flow of input-output is best characterized by a random walk process. This indicator measures how easily a node can be reached from another node anywhere in the network by a random walk process (Oldham and al., 2019). By adapting it to a production network context, the random walk centrality captures the speed and frequency with which a sector is affected during the process of shock transmission in the economy, thereby making it particularly appropriate for the assessment of sector's responses to an economic shock occurring elsewhere in the network (Joya and Rougier,2019).

The Random Walk centrality of sector i is then defined as follows:

$$RWC_i = \frac{n}{\sum_j H(j,i)} \tag{14}$$

Whith H(j,i) denoting the mean first passage time (MFPT). For a random walker, the MFPT indicates the expected number of steps it takes when moving from sector j to sector i for the first time.

In our analysis, we will mainly focus our attention on the analysis of the above mentioned centrality measures, in that they will allow us to ascertain how a sector's position as a direct and indirect supplier (consumer) of intermediate inputs would affect its response to exogenous shocks.

However, the intuitive mechanism behind our analysis suggests that we should also investigate another category of network indicators that reflect the relative position of a given sector in a neighborhood of interconnected sectors, namely local density indicators.

3.1.4 Local density indicators of production networks

These network indicators are worth to be considered in our analysis as they would allow us to investigate how a sector's position within sub-networks influences its response to sectoral shocks. Joya and Rougier (2019) suggest that shocks to sectors located in dense sub-networks are more likely to dissipate through alternative paths thereby insuring

In fact, by measuring the diversification of connections around a node/sector, these measures were used to investigate substitution effects in Joya and Rougier (2019)

As such, We follow Joya and Rougier, (2019) and compute two local density measures, the local clustering coefficient and the average neighboring degree.

The local clustering coefficient metric measures the probability that two nodes are connected knowing that they have a neighbor in common. The rationale behind this measure follows from the concept of transitivity, whereby if node A is connected to node B, and node B is connected to node C, then there is an increased probability that node A is also connected to node C, resulting hence in a closed triad (Joya and Rougier,2019).

This measure captures, therefore, the proportion of closed triangles present in the network and is defined as follows:

$$CC_i = \frac{(W^{\frac{1}{3}})^3{}_{ii}}{d_i^{in} d_i^{out} - d_i^{\leftrightarrow}} \tag{15}$$

The clustering coefficient can be used, also, to identify missing links between the neighbors of a node known as "Structural Holes"(Newman, 2010). As they reduce the number of alternative paths of transmission of a traffic of any kind, Newman (2010), these structural holes could act as shock propagation inhibitors in our case.

Therefore, we expect sectors with small local clustering coefficients to face relatively lower indirect shocks.

The second local density measure we consider in our analysis is the average degree of neighboring nodes. This network statistic informs us about the level and density of connectedness of neighboring sectors. A sector with a high AVN is one that connects to others that have diversified input and output linkages within the economy.

According to the diversification argument, such an economic structure leads to a mitigation effect, as alternative supply and demand linkages would dissipate sectors' independent shocks (Lucas, 1977; Xu et al., 2011; Koren and Tenreyro, 2007; Joya and Rougier,2019).

The Average degree of neighboring nodes is formulated as follows:

$$AVN_i = \frac{1}{|N(i)|} \sum_{J \in N} k_j \tag{16}$$

3.2 Data

In this paper we used the first wave covid-19 supply and demand shocks data to compute the indirect effects.

Since our objective is to calculate the indirect effects over the short run, we have taken as supply shock the labor supply shock, which corresponds to the percentage of employees who stopped working during the first wave of the lockdown in Tunisia. Our variable stems from a household survey conducted jointly by the National Institute of Statistics and the World Bank from April 29 to May 8, 2020 among a panel of 1,369 representative households of the Tunisian population.

In order to assess the indirect effects of the initial demand shocks, we made use of an enterprise survey data carried out following the first wave of the covid-19 crisis, april and may 2020, on a sample of 1,200 firm in the context of the CORES project aiming at evaluating the impact of the pandemic on Tunisian firms. To derive the indirect demand shocks we used a The percentage change in total demand addressed to firms. Data were aggregated and mapped to the sectoral classification of Tunisia's 2018 input-output table.

To compute the inverse of the Leontief matrix as well as the different general and sectoral network characteristics, we used the 2011, 2015 and 2018 Tunisian input-output tables from the Tunisian National Institute of statistics.

4 Results and Discussion

In this section we present the results of the different methodologies presented above to compute the indirect impact of supply and demand shocks related to the covid-19 crisis on the Tunisian economy.

4.1 Indirect Covid-19 supply and demand shocks

Using the Tunisian input-output table (2018), we compute, following the theoretical results of Acemoglu et al. (2016), the transmission mechanisms of supply and demand side shocks, namely, downstream and upstream linkages.

• Supply side shock

During the first wave of the Covid-19 pandemic, social distancing measures taken by the Tunisian government led to an unprecedented labor supply shock, importantly in non-essential sectors with a labor force that cannot work from home.

Though we take labor supply shock to be our supply shock variable. In fact, since we aim at estimating the first wave impact of the covid-19 crisis, and while one of it is main outcomes was labor supply shock, we take it to be our supply shock variable. In fact, our approach is in line with several studies that evaluated the supply side impact of the covid-19 pandemic but also of previous ones (del Rio chanona et al. 2020,)

Using, a survey conducted by the Tunisian National Institute of Statistics during the first wave of the pandemic we compute the share of workers who lost their jobs because they belonged to non-essential sectors and were unable to work from home .

Figure 1 shows that labor supply shock is heterogeneous across sectors. Indeed, the most affected ones are hotels and restaurants and public and private education for services with almost 80 per cent of labor loss. For the non-manufacturing sectors, we find Petroleum and natural gas and construction as the ones with the largest labor loss with 80 and 60 per cent respectively, and for the manufacturing, Electrical and machinery, textile, construction materials ceramic and glass face a labor reduction above 60 per cent.

Though important, these sharp declines in labor supply represent only sector's direct (own) shock. As emphasized earlier in this paper, sector's output is a function not only of its own shock but also of indirect shocks, e.g the weighted sum of shocks to all other sectors with the element of the Leontief inverse matrix as weights.

As such, by combining the vector of labor supply shock by sector with the matrix of downstream linkages, mimicking exactly equation (1), we derive indirect labor supply shocks .

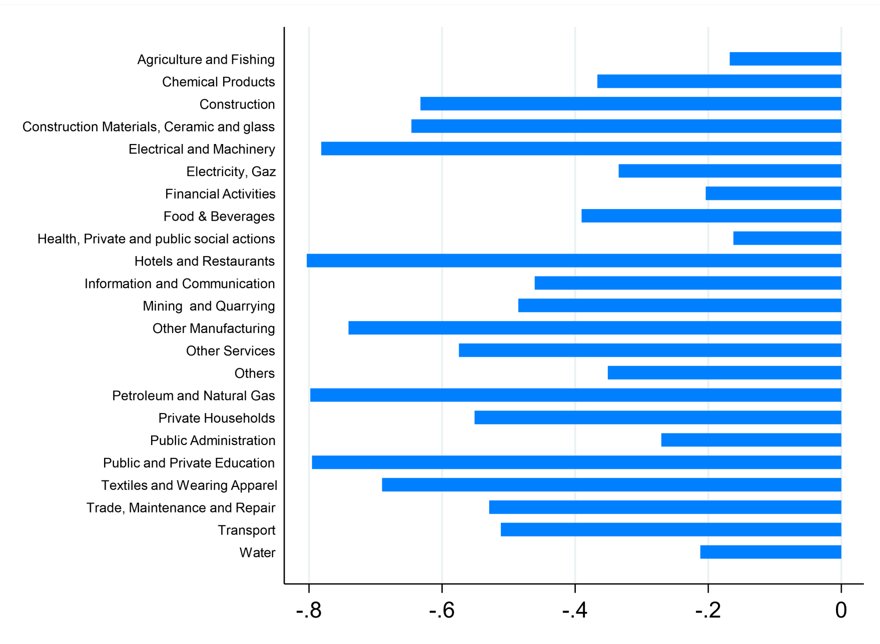


Figure 1: Labor Supply Shock

Figure (2) shows the existence of important indirect supply shocks, unobserved while not taking into account sectoral interactions. Though economic sectors bear not only their own labor supply shock but also their supplier's labor shocks.

However, as can be seen, the magnitude of these indirect shocks is not, always, more important than sector's own shocks as argued by Acemoglu et al. (2016). For example, we notice that for the Information and communication, Electricity and Gas, and Water sectors, the indirect shocks are greater than the own shocks, whereas sectors such as Petroleum and natural gas, Electrical and Machinery, and textile face a much larger direct labor supply shock.

In an attempt to explain the obtained results, we make a comparison between the sectors for which the indirect shocks are greater than their own shocks.

The large indirect labor supply shocks that face these sectors can be explained in part by their important position as consumers of inputs in the production network. However, this could not be the case of the Water sector even when the output impact of the indirect labor shock is twice its direct impact. This is due to its relatively small own shock with a decrease of only 21 per cent.

While the covid-19 crisis has the particularity of being both a supply and a demand shock, we estimate in the following section, sector's direct and indirect demand shocks.

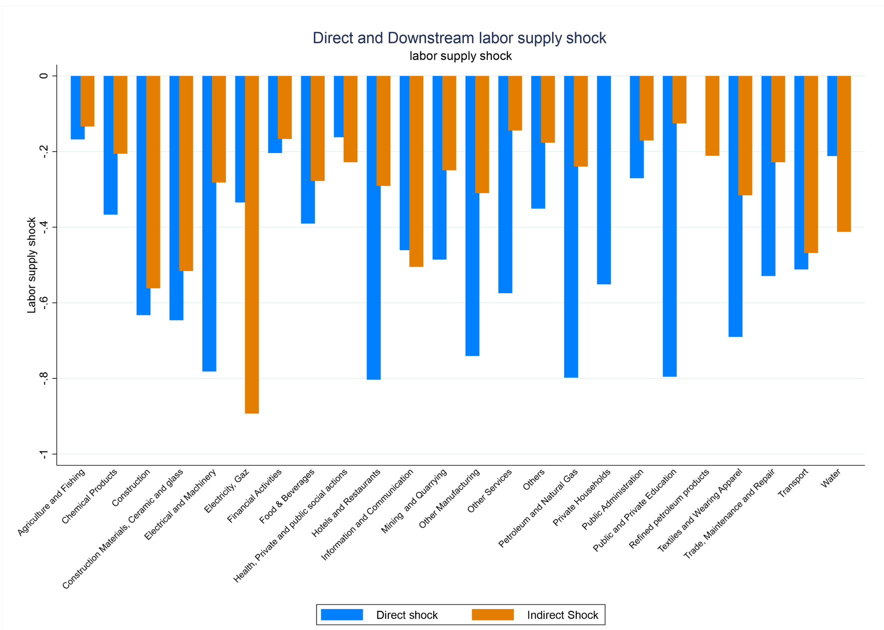


Figure 2: Direct and Downstream labor supply shock

• Demand side shock

To measure the extent of direct and indirect demand shocks faced by the Tunisian economy, we use a survey conducted as part of a CORES project to assess the vulnerability of Tunisian firms to shocks from the covid-19 pandemic. We use the percentage change in demand addressed to Tunisian firms during April and May 2020 as a proxy for our demand shock variable. By aggregating the data at the 2-digit level and mapping it to the Tunisian 2018 input-output classification, we derive the direct demand shock.

Figure (3) shows that demand shocks were also heterogeneous across sectors. The drop in demand was most severe during April than May as at the end of this month containment measures began to ease. We find negative demand changes in all sectors, with the largest drops observed in construction materials, ceramic and glass, textile and the other manufacturing sectors.

On the other hand, sectors that involve consumers' contact have also suffered very significant negative demand shocks, essentially the hotel and restaurant sector, transport, trade, repair and maintenance, and transport sectors. We note that sectors such as hotels and restaurants and construction have been subject to very important both supply and demand negative shocks.

These estimates, while do not distinguish between final and intermediate consumption, are consistent with estimation results of sectoral demand shocks in the early phase of the covid-19 pandemic (del Rio-Chanona et al. 2020; Muellbauer, 2020; OECD, 2020).

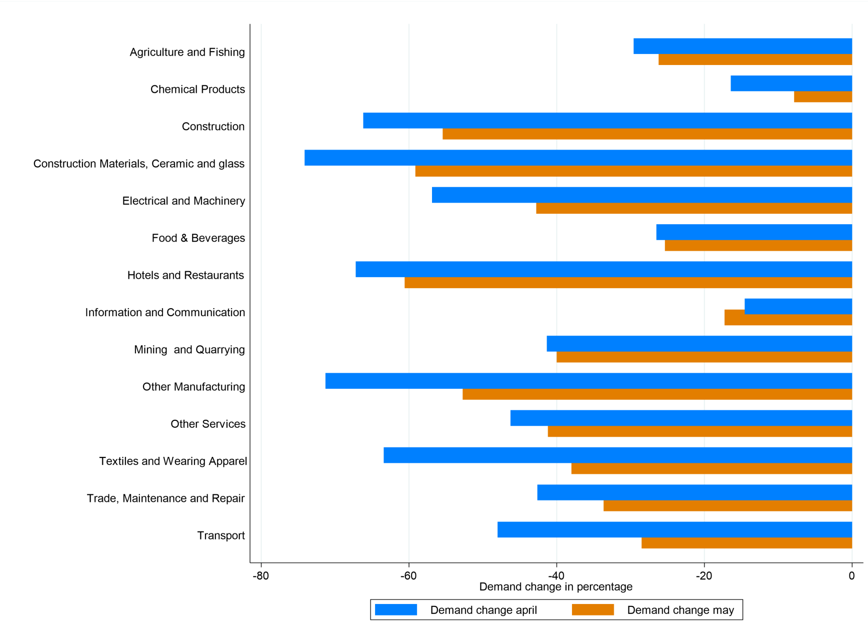


Figure 3: Demand change in April and May 2020

Sectors hit by negative demand shocks, by adjusting their production levels, reduce their demand for inputs, thus affecting their suppliers, who in turn reduce their demand for inputs from their suppliers and so on. To quantify this upstream propagation, we combine the vector of sectoral demand shocks with the matrix of upstream linkages.

Figure 4 shows that the different sectors experience important indirect demand shocks even when they are not directly confronted to demand shortages, as is the case for the financial activities sector. However, only the Chemical and, Mining and quarrying sectors show indirect shocks larger than direct shocks. Indeed, the mining and quarrying sector is an important supplier of inputs to two sectors that have experienced strong demand shortages, the construction and CMCG sectors with a drop of around -74 and -66.2 per cent respectively.

Overall, we notice that indirect shocks were less important than direct shocks for both supply and demand. This can be explained by weak downstream and upstream linkages compared to a more developed economy. However, these results highlight the importance of input-output linkages in determining sectors' output, by propagating and amplifying first-order (direct) shocks to sectors. It is extremely important to take into account these transmission channels when assessing the impact of different shocks on sectors' output. Moreover, we notice that sectors that play an important role in the production network as suppliers or consumers of inputs constitute an important source of transmission of shocks. We further analyze this statement in the next section where we evaluate the role of the structural properties of the Tunisian production network in shaping sectors' output.

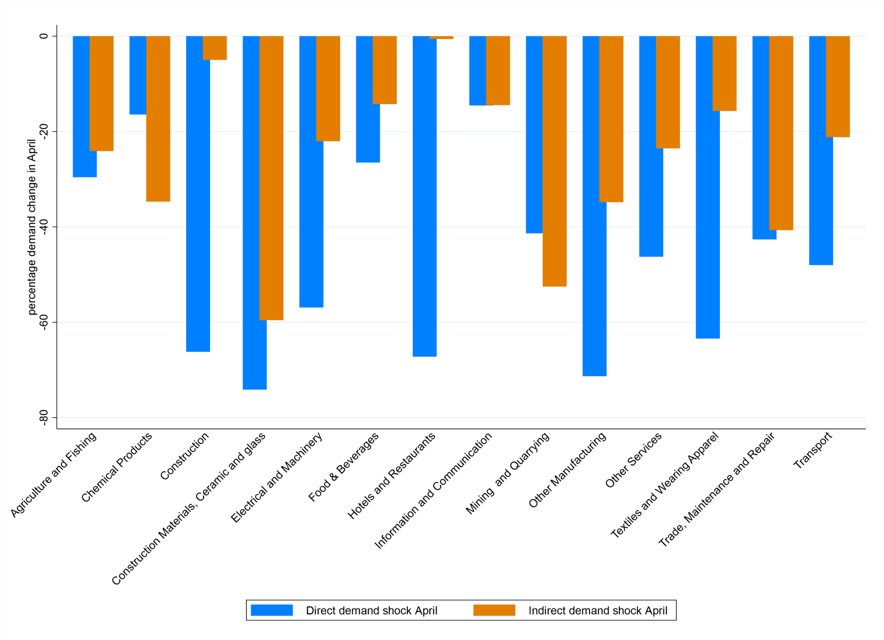


Figure 4: Direct and Upstream demand shock

4.2 Properties of the Tunisian Production Network

In this section we present the structural features of the Tunisian production network. Recall that an aysmmetric structure of indegrees or outdegrees reflects the existence of relatively important sectors as consumers or suppliers of input. This structure enables the transformation of sectoral shocks into aggregate fluctuations on a macroeconomic scale (Acemoglu et al. Carvalho. 2014), however, their effects on the individual sectors have not been explored so far.

To do so, we adopt a network approach and analyze the main features of the Tunisian production network using the 2018 input-output table from the Tunisian National Institute of Statistics. Sectors constituting the production network are thus assimilated to nodes and the input flows from the supplier sectors to the costumer sectors are represented by directed edges.

We plot the network representation of the Tunisian intersectoral linkages by considering the unweighted version of the input-output matrix.

Figure 5 shows that the Tunisian production network admits few important sectors in terms of the number of sectors to which they supply intermediate inputs, defined by the unweighted outdegree score, relatively to other sectors. The most important sectors, are Electrical and machinery, Other services and Other manufacturing sectors, and to a lesser extent Financial activities, Transport and chemical product sectors. This gives us a first glance about the asymmetric structure of the Tunisian production network, which we further investigate in what follows.

Another important network statistic, the density , informs us about the degree of connectedness of sectors (nodes) within the production network. This measure ranges from 0 to 1 and the closer it is to 1, the denser the network is, i.e. the more connected the sectors are to each other.

The Tunisian production network displays a density of 0.23, which is relatively low with regard to the level of disaggregation considered. In fact, Carvalho (2014) finds that the density of the US production network, represented by an input-output table with 417 sectors, is 0.03. This low density is explained by Carvalho (2014) by the high level of disaggregation of the US input-output table.

To better characterize the structure of the Tunisian production network, we compute two metrics that are also fundamental in network analysis and translate how quick something will spread in the network, namely the distance and diameter. The distance between two nodes in a given network is defined by the length of the shortest path while the diameter is defined by the largest distance between any two nodes in the graph, (Jackson, 2008). Low values of these two measures, relative to the size of the network, are indicative of the presence of what the network literature characterize as a small-world network (Carvalho, 2014). With a long average distance of 2 and a diameter of 5, relative to the level of disaggregation of the Tunisian production network, we cannot consider the Tunisian production network as a small world through which a shock to one sector propagates quickly to the rest of the economy.

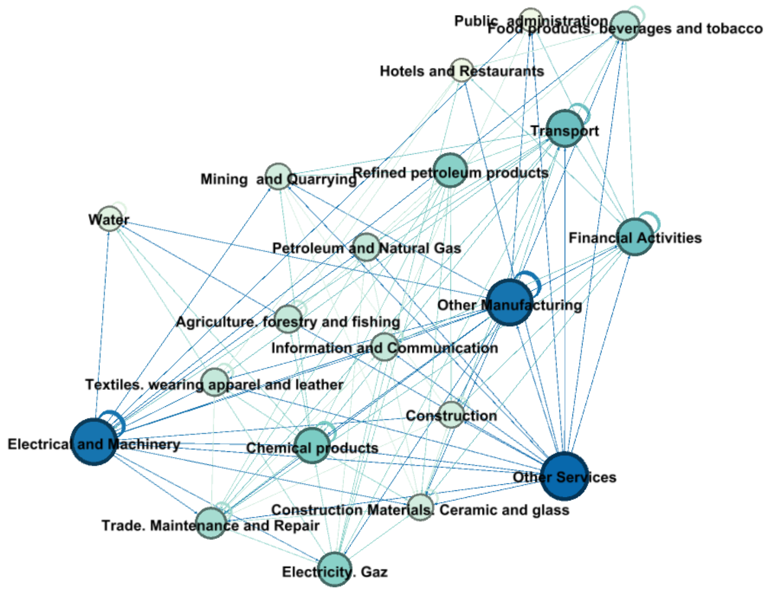


Figure 5: Tunisian Production Network

Although preliminary results show that the Tunisian production network is weakly connected, further analysis of sector's in and out degrees' distributions as well as more intricate centrality measures are required to assess whether or not the Tunisian production network displays an asymmetric structure in terms of sector's direct and indirect suppliers and consumers of intermediate inputs.

Using Tunisian input-output tables for the years 2011, 2015 and 2018 from the Tunisian National Institute of Statistics, we analyze the variation of the weighted indegrees by estimating the empirical density using the non-parametric method as in Acemoglu et al (2012).

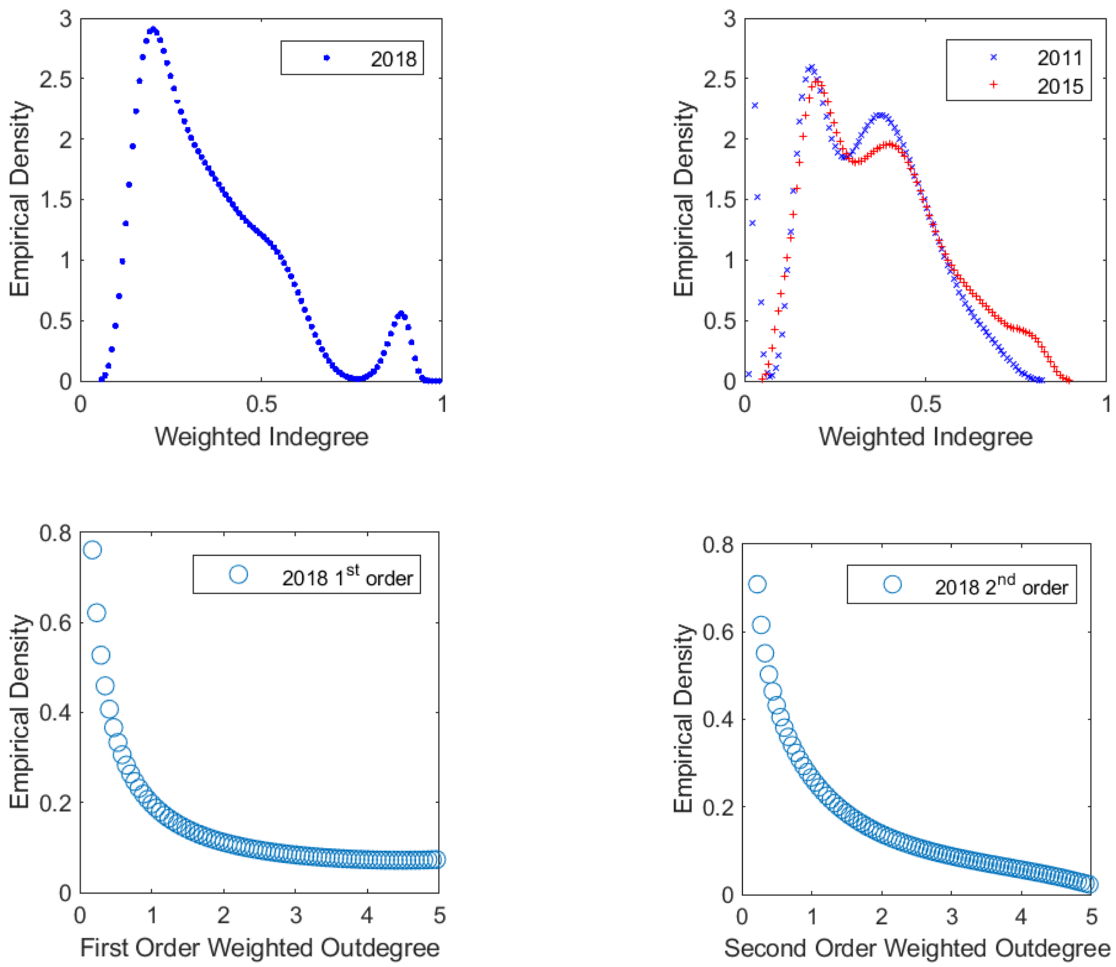


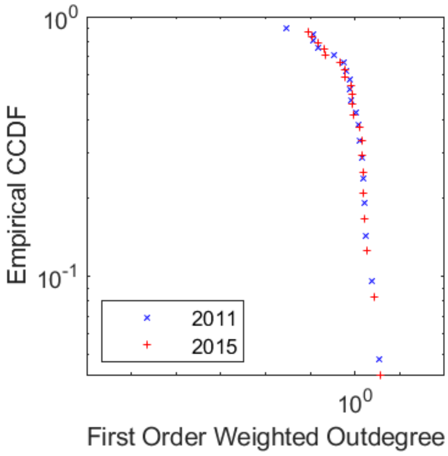
Figure 6 shows that intermediate input distribution has not changed between 2011 and 2018 with an average input share across sectors that varies between a minimum of 0.32 in 2011 and a maximum of 0.4 in 2018 leading to an average across years of 0.36. We notice that the Tunisian economy admits low shares of intermediate inputs in their production technologies with nearly 80 per cent of sectors having their indegrees concentrated around the mean (within one standard deviation of the mean input share.)

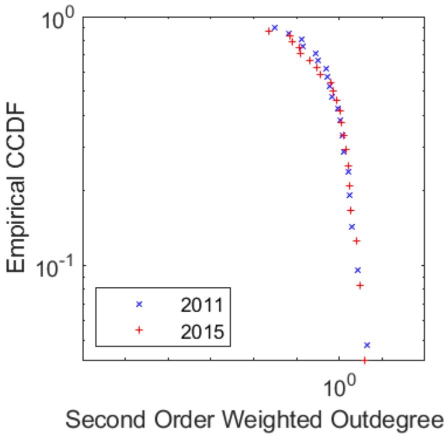
We also analyze the evolution of the distribution of first and more specifically second-order outdegrees and examine whether it exhibits an asymmetric pattern reflecting the existence of few key sectors playing the role of general input suppliers ensuring the transmission of shocks within the network.

Figure 7 shows the non-parametric estimation of the empirical first and second order outdegrees. We clearly notice that the distribution of the weighted outdegrees is completely different from that of the weighted indegrees.

The two panels of Figure 7 show an asymmetric distribution of the first and second order outdegrees with a right tail. In fact, as demonstrated by Acemoglu et al. (2012), such a skewed distribution translates the high variability in the roles that sectors play as direct and indirect suppliers of inputs to the economy.

To further investigate such a disparate distribution of the outdegree sequences, we follow Acemoglu et al. (2012) and Carvalho (2014) and estimate the counter cumulative distribution





functions of the outdegree sequences using the Nadarya-Watson kernel regression approach and plot it on logarithmic scales.

The almost straight-line forms in Figures 8 and 9 illustrates a significant power-law empirical distribution of both first and second order outdgrees, reflecting their high variability across sectors. On the other hand, and according to the theorem developed by Acemoglu et al. (2012) this form of distribution (approximated by a power law) indicate that sectoral shocks would not wash out and would rather propagate to the rest of the economy.

These results translate the existence of key sectors that provide general purpose inputs, which are themselves connected to important input suppliers, forming, hence, a kind of hub-like sectors that act as the main propagator and amplifier of sectoral shocks within production networks (Gabaix 2011; Acemoglu et al. 2012; Carvalho 2014). Though, despite the weak connectivity of the Tunisian production network, reflected by its low density, the above results reveal that its properties ensure the propagation of sectoral shocks across the network.

4.2.1 Sectors' Network characteristics

In this section we have derived sectors' different centrality and local density measures.

Network Statistics Correlation Matrix Table 1 presents the correlation matrix between the first and second order centralities as well as the local density measures. It shows important correlations between first and second order centrality measures.

On the one hand, we notice that first and second order outdegrees, capturing important direct and indirect supplier of inputs, are positively correlated with the katz Bonacich centrality. While, from a demand side perspective, the first and second order indegrees show a strong positive correlation with the page rank and random walk centrality metrics.

We also underline the high correlation between first-order indegrees and the second-order indegree measure that we developed, attesting, although not necessarily always the case, to its reliability.

Thus, we can conclude that sectors that are important as direct suppliers (consumers) of inputs are also, typically, major indirect suppliers (consumers) of inputs. These results are in line with the findings of Oldham et al. (2019).

On the other hand we notice that the local density measures are less correlated with the first and second order centrality measures.

For instance, we find that the average degree of a node's neighbors is negatively correlated with the centrality measures capturing key supplier sectors. Meaning that key supplier sectors tend to be surrounded by other sectors that do not have diversified linkages with the rest of the economy.

On the other hand, we notice that the local clustering metric displays higher correlation coefficients with the different centrality measures. They are negatively correlated with key consumer sectors and positively correlated with the predominant input suppliers. This result presumes that supply chains are more likely to form clusters within the economy than demand chains.

Table 1: Network Statistics Correlation Matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
1 Indegree	1.000								
2 Outdegree	-0.388*	1.000							
3 Second-Ind	0.835*	-0.407*	1.000						
4 Second-Out	-0.423*	0.944*	-0.404*	1.000					
5 KBC s	-0.403*	0.975*	-0.404*	0.991*	1.000				
6 RWC	0.635*	-0.030	0.715*	-0.090	-0.085	1.000			
7 PR	0.335*	0.239*	0.472*	0.123	0.162*	0.732*	1.000		
8 AVN	-0.053	-0.271*	-0.013	-0.240*	-0.250*	-0.065	-0.025	1.000	
9 CC	-0.425*	0.423*	-0.462*	0.500*	0.471*	-0.357*	-0.510*	0.090	1.000

Note:

Key Tunisian Production Network Sectors: In the table below we identify the top 5 key sectors as direct and indirect suppliers and consumers of inputs in the Tunisian production network. We notice that the various centrality measures report almost the same sectors as important to the Tunisian economy.

From a demand perspective, the Trade, Maintenance and Repair sector shows the highest first- and second-order centrality measures, making it the largest consumer of inputs within the Tunisian production network. This is in line with the findings of Blochl et al. (2011), who report the Wholesale and Retail trade as the sector with the most important random walk centrality in a set of different developed and emerging countries. In Tunisia this sector is followed by the Construction, Construction Materials Ceramic and glass, Water and the Other services sectors.

From the supply side, we identify the Other services, Electrical and Machinery, Other Manufacturing, Chemical products and Refined Petroleum products as the major direct and indirect suppliers of inputs.

According to Acemoglu et al. (2012,2016), these sectors serve as a channel for the propagation and amplification of independent sectoral or firm level shocks. Hence, in crisis such as the covid-19 pandemic, policy makers in Tunisia should implement bailout measures that target first and foremost these sectors.

Regarding Sectors surrounded by the highest average neighboring degree is the Hotels and restaurant sectors

Table 2: Sectors' Network Characteristics

	First Order Centrality		Second Order Centrality					Local Density	
Sector	**Indegree**	**Outdegree**	**2nd-Ind**	**2nd-Out**	**KBC**	**RWC**	**PR**	**AVN**	**CC**
Trade MR	1.00	0.49	0.59	0.51	0.03	0.07	0.12	9.12	0.10
Elect. Gaz	0.88	0.87	0.16	0.77	0.04	0.04	0.03	14.29	0.27
Food. Beve	0.58	1.67	0.18	0.93	0.05	0.01	0.03	8.06	0.44
Construction	0.56	0.21	0.23	0.10	0.02	0.04	0.12	23.11	0.12
Transport	0.52	0.85	0.16	0.99	0.04	0.03	0.04	20.48	0.39
CMCG	0.51	0.62	0.22	0.23	0.03	0.03	0.05	14.81	0.37
Water	0.44	0.45	0.21	0.34	0.03	0.02	0.08	29.90	0.26
H and R	0.41	0.15	0.21	0.10	0.02	0.02	0.03	34.74	0.04
Infor and C	0.41	0.91	0.16	0.87	0.04	0.03	0.07	26.13	0.39
Mining nd Q	0.35	0.25	0.10	0.16	0.02	0.01	0.02	11.82	0.28
Other Manuf	0.35	1.65	0.11	2.00	0.06	0.01	0.02	16.93	0.63
Textiles	0.31	0.78	0.10	0.58	0.03	0.01	0.04	32.54	0.42
Elect and M	0.27	2.35	0.08	3.30	0.08	0.00	0.01	14.38	0.72
Chemical.P	0.26	1.90	0.08	2.45	0.07	0.01	0.02	19.43	0.60
Agricu and F	0.22	1.06	0.10	1.43	0.04	0.01	0.02	14.71	0.61
Finan Activ	0.21	1.32	0.05	1.23	0.05	0.01	0.02	22.09	0.71
Ref petrol	0.20	1.36	0.04	1.02	0.05	0.01	0.01	21.67	0.66
Other Serv	0.18	3.85	0.05	3.63	0.10	0.04	0.17	7.64	0.10

Note: Table summarizing the network characteristics for different sectors based on first and second order centrality measures and local density.

Finally and applying a pairwise correlation analysis between the indirect Covid-19 supply and demand shocks and the different centrality and local density measures, we investigated how sector's network characteristics have influenced their respective responses to these shocks.

Figure 9 shows a positive correlation between sectors' indirect supply shocks and their positions as consumers of inputs. This result support our assumption that sectors located downstream within the production network are more likely to bear the highest spillover effects from supply shocks.

However, we notice that this correlation is more important for the first order centrality measure, the indegrees, than the second order centralities with the most significant being the random walk centrality measure. This could be explained in part by differences in the intensities of the initial sectoral supply shocks.

On the other hand, we find a negative correlation between key input supplying sectors and the indirect supply shocks they encounter.

Indeed, we note that the upstream sectors along the production chain, with high first and second order outdegrees and katz Bonacich centrality coefficients, tend to face lower indirect supply shocks.

This result is quite consistent with the theoretical and empirical findings of Acemoglu et al. (2016), which stipulate that, within production networks, supply shocks propagate mainly downstream, i.e., form supplier sectors to customer sectors.

Regarding local density measures, Figure 9 indicates that they are less correlated with the indirect supply shock than are the different centrality metrics.

We notice that sectors located in clusters are more resilient to the cascade effects of supply shocks. This is a fairly coherent result as clusters are more likely to be formed within supply chains that, as mentioned above, themselves face smaller indirect supply shocks. This finding is also consistent with the study of Dai et al. (2021) who show that firms' clustering in China helped stabilising supply chains and reducing their vulnerabilities to Covid-19 shocks.

On the other hand, a reverse (positive) pattern is observed for the average degree of neighborhood, implying that indirect supply shocks affect more sectors surrounded by well-connected neighbors. In that sense, dense sub-networks serve as a propagation channel of supply shocks to adjacent sectors when these latter consists of major input consumer sectors.

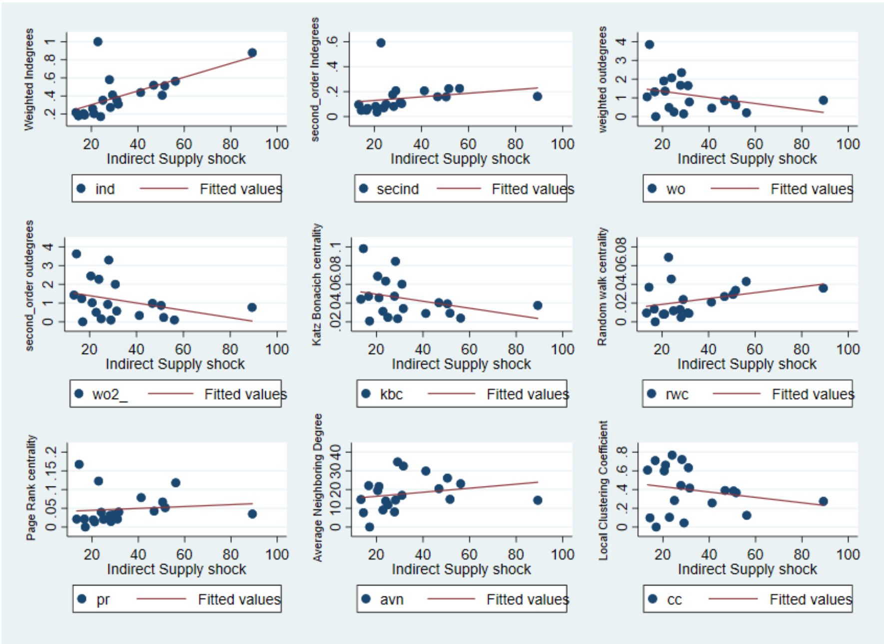


Figure 9: Indirect supply shocks and Network Statistics

Turning to the interplay of indirect demand shocks with sectors' centrality characteristics, Figure 10 reveals the absence of a correlation between the two. In fact , while we expected indirect demand shocks to affect more key supplier sectors, sectors located upstream within production networks due to cascade effects.

However, we note a weak but significant correlation between the spillover effects of demand shocks and sectors' positions within sub-networks.

We find local clustering coefficients to be positively correlated with indirect demand shocks. Thus, being strongly connected to their neighbors, key supplier sectors, were more prone to greater spillover effects of demand shocks. In which case, clustering no longer ensures sectors' resilience but rather act as a contagion source by transmitting the initial demand shocks from downstream sectors.

Meanwhile, and as expected, we find sectors' featuring higher average neighboring degree to face lower indirect demand shocks. Indeed, the diversification of connections around key input consuming sectors in sub-networks helped mitigating the transmission of demand shocks to these ones.

Once again, this finding supports the fact that dense sub-networks, depending on the nature of the shock, could dampen the propagation of shocks, their transmission to the rest of the economy, or even their amplification. This matches closely the outcomes in Joya and Rougier (2019), who demonstrate that shocks to sectors in well connected sub-networks washed out due to a substitution effect.

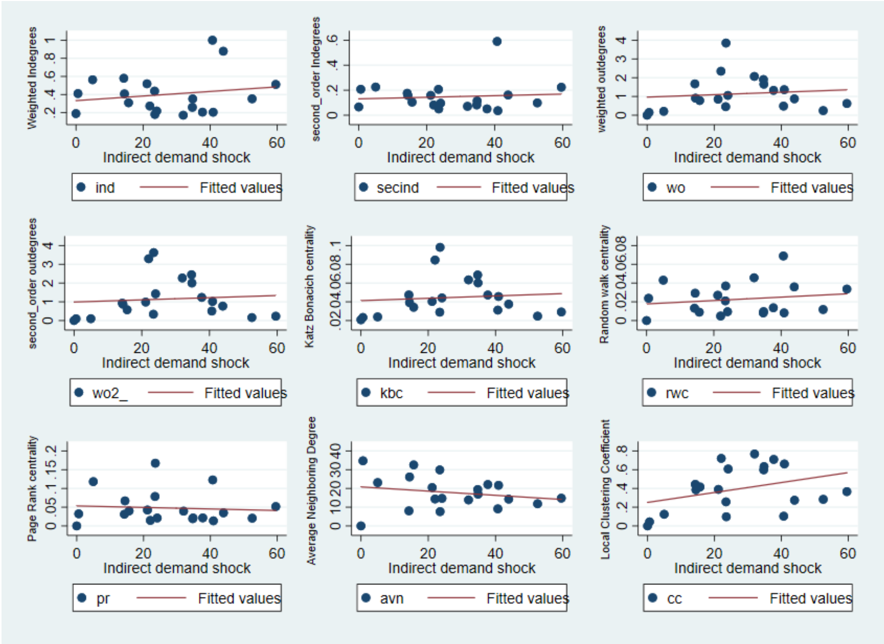


Figure 10: Indirect demand shocks and Network Statistics

To summarize, the results of our pairwise correlation exercise provide evidence on the existence of a relationship between sectors' network characteristics, as well as, shock's nature with sectors' responses to indirect shocks propagating through input-output linkages.

Our findings are in line with Acemoglu et al. (2016)' assessments who demonstrate that supply shocks propagate mainly downstream while demand shocks transmit principally upstream, from customer sectors to supplier sectors. With key consumer sectors facing higher indirect supply shock while major input supplier sectors within sub-networks being more vulnerable to the spillover effects of demand shocks. We highlight thus the importance of considering and identifying key consumer sectors within the demand chain and not only focusing on the supply chain's main input suppliers in times of crisis.

We noticed, however, the absence of a correlation between sectors' first and second order centrality measures and indirect demand shocks.

We found also evidence of a mitigation effect along with the contagion effect that arises from the interplay of sectors' positions within sub-networks with the nature of the initial shocks. In that, we support the results in Joya and Rougier (2019) that production networks can both transmit and dissipate independent sectoral shocks. Therefore, from a network perspective, the diversification argument (Lucas, 1981) can hold when analysing the propagation of sectoral across input-output linkages.

Hence,in examining the sectoral but also the macroeconomic implications of individual shocks propagating through input-output linkages, a more in-depth analysis of sectors' complex network properties is crucial to assess the extent to which the spillover effect outweighs the diversification effect.

5 Conclusion

In this paper, we investigated the existence of a relationship between sectors' network properties and their responses to the spillover effects of the Covid-19 shocks. Drawing on the work of Acemoglu et al. (2016), we first computed the indirect effects of the supply and demand shocks. Then using graph theory techniques, we derived sectors' centrality and local density measures and performed a pairwise correlation analysis.

The results of our correlation analysis exercise were in line with recent contributions on the way in which network interconnections propagate sectoral shocks and impact economic outcomes. More specifically, we found central sectors, from a demand side perspective, to be more vulnerable to the cascade effects of supply shocks while key supplier sectors to bear higher indirect demand shocks.

This finding matches perfectly the propagation pattern in Acemoglu et al., (2016) where supply shocks propagate mainly downstream while demand shocks follow, rather, an upstream pattern. Also, the existence of a relationship between key input consumer sectors, those with high random walk and page rank centralities, and indirect supply shocks demonstrate that it is of major importance to consider not only sector's position within supply chains, as we can find in the existent literature, but also their respective positions along demand chains. In other words, we can conclude to the fact that a sector's exposure to indirect shocks depends on both its network position and characteristics and on the shock's nature.

Moreover, the interaction of sectors' features within sub-networks, with the initial supply and demand shocks has resulted in a mitigation effect along with the contagion effect for the different sectors. This implies that the structural characteristics of the production network can simultaneously transmit shocks but also dissipate them through alternative paths. We thus join Joya and Rougier (2019) who demonstrate that shocks to sectors located in dense sub-networks tend to wash out while shocks to central sectors propagate and get amplified. We add to this by presuming that the trajectory and impact of a shock are also driven by the type of the shock itself.

Therefore, in order to estimate the extent to which sectors' network characteristics impact their responses to shocks taking place anywhere in the economy, a more in-depth analysis that takes into account the two effects is required. This would allow us to identify the conditions under which the spillover effect prevails over the mitigation effect and vice versa.

From a policy perspective, these results could be of great interest to decision-makers as they would allow them to better identify the most vulnerable sectors, from a supply and demand side perspective to exogenous supply and demand shocks and thereby to design and implement the most appropriate measures.

While being only the result of a correlation analysis, this paper has provided important insights regarding a relationship that has been overlooked in the recent literature on production networks and that could be further investigated through a more accurate econometric analysis.

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