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Linking FDI Network Topology with the Covid-19 Pandemic

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Abstract

Globalization has considerably increased the movement of people and goods around the world, which constitutes a key channel of viral infection. Increasingly close economic links between countries speeds up the transfer of goods and information, and the knock-on effect of economic crises, but also the transmission of diseases. Foreign direct investment (FDI), in particular, establishes clear ties between countries of origin and destination, and it is along these chains that contagious phenomena can unfold. In this paper, we investigate whether countries with more central positions in the global production network have higher COVID-19 infection and mortality rates. We merge data on EU-28 outward FDI with data on COVID-19 per capita infection and death rates to analyze their association with the topology of the FDI network. Our estimates reveal that countries most exposed to the COVID-19 outbreak are those characterized by a more central role in the global production network. This result is robust to the use of alternative measures of network centrality, and to the possible influence of the 2008 financial crisis on the structure of the global production network. We also find that exposure to the pandemic increases with the centrality of a country in the FDI network of certain industries, including business machinery and equipment, business services, real estate, tourism and transport.

Key words: Foreign direct investment, economic networks, centrality measurements, COVID-19, pandemic

JEL codes: F23, D85

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1 Introduction

From the early days of the outbreak in Wuhan, it was clear that a local event could have global economic consequences. The Hubei region, with its population of 60 million, is an important industrial district where semiprocessed parts are manufactured for the automotive and electronics industries. The stoppage of its production lines rippled along the global value chain (GVC). Meanwhile, the lockdown imposed in China led to a freezing of business investments and a reduction in Chinese household consumption, with a significant impact on Chinese imports. This local crisis turned into a worldwide event through the global production network. It is worth recalling that the Special Program for Research and Training in Tropical Disease examined the possible links between globalization and infectious diseases in 2004 (World Health Organization, 2004). Its report focuses on changes in the nature of infections, the effects of deforestation or the lack of clean water, as well as on the role of international trade that was increasing the economic linkages between countries. We argue that a greater degree of international integration implies that a shock in one country can spread to the others through trade and global production linkages.

The literature taken for reference associates systemic risk (a health risk in the case in point) with the topology of networks. In its various formulations, systemic risk refers to the existence of a domino effect: an initial cause (the emergence of a virus) generates a series of negative effects (on public health). This risk may or may not be facilitated by the structure of the network linking the various actors (different countries in our case) to each other. For our purposes, therefore, systemic risk refers to a situation in which instability in one country leads to instability in another (Recchioni and Tedeschi, 2017). There are two phenomena related to systemic risk that have already been studied extensively in the analysis of networks: the propagation of damage through the network; and the spread of epidemics. Zhao et al. (2004) show that scale-free networks exhibit exceptional resistance to random damage, but can suffer badly from intentional attacks. Pastor-Satorras and Vespignani (2001) also demonstrate that scale-free networks facilitate the propagation of infections, bugs, and fake news.

These different effects stem from the diffusion and propagation properties of scale-free networks, and particularly from the hierarchies within them. Once central hubs (nodes with many connections) have been affected, an infection will spread to the (lesser) nodes of the whole network, with a clear cascade effect. This idea has already been used in economics, mainly to analyze how network topology has a systemic impact on credit-debit chains and the interbank network (Berardi and Tedeschi, 2017; Lenzu and Tedeschi, 2012), and other financial networks (Hautsch et al., 2015; Acemoglu et al., 2015).

The literature has also dealt with the relationship between health risks and the connections between actors. Brockmann and Helbing (2013) examine how disease spreads through transport networks. Instead of considering geographical distance, they analyze the effects of an "effective distance": two different places are closer if the link between them is stronger. Using data concerning three different epidemics (SARS in 2003, H1N1 in 2009 and the outbreak of *Escherichia coli* in Germany in 2011), they show how a network's topology can help predict the arrival of a disease and facilitate or impede the contagion. Along the same lines, Ruan et al. (2015) also show that the infrastructure of a network matters. The speed with which one city can be reached from another is more important than the geographical distance between the two. The spread of an epidemic then depends both on this speed and on the frequency of travel from one place to the other. Here again, it is the structure of the network that determines the pattern of the epidemic's diffusion.

Over the course of 2020, the arrival on the world scene of COVID-19 has made it necessary to analyze in more depth how epidemics spread, especially in order to identify the most effective containment policies. Kraemer et al. (2020) use human mobility data (the travel network) to examine the effectiveness of measures adopted in China to contain the spread of the virus. They find that both travel restrictions and mobility controls substantially mitigated the diffusion of the epidemic. In a similar vein, Chinazzi et al. (2020) look at how restricting people's movements affected the spread of COVID-19 in China. Using a network model, they show that locking down early in the outbreak could reduce (or delay) the spread of the disease both nationally and internationally.

Our paper contributes to this line of research. Assuming that COVID-19 spreads throughout the global production network, we try to ascertain whether its diffusion correlates with features of the network's topology. To be specific, we examine whether, ceteris paribus, a country's centrality in its FDI network influences its SARS-Cov2 per capita infection and death rates.

To build our centrality measures, we apply network analysis to data on countries' outward FDI flows. Network analysis has been used in various fields of economic theory, and is establishing itself as a key tool for understanding connections between agents. In the empirical literature, it has been applied to study the structure and functioning of the credit market (De Masi et al., 2011; Battiston et al. 2012), the interbank market (Iori et al., 2008), financial investments (Garlaschelli et al., 2005), and world trade (Fagiolo et al., 2009; De Benedictis and Tajoli, 2011, 2018; Abbate et al., 2018), and to delineate the structure of global value chains (Criscuolo and Timmis, 2017). Scholars have applied network theory to FDI in order to: investigate agglomeration phenomena (Alfaro and Chen, 2014); examine the relationship between FDI and migration (Garas et al., 2016), or between FDI and trade (Metulini et al., 2017); and match ownership with firms' control all over the world (Rungi et al, 2017). Focusing on firms, De Masi et al. (2013), and Joyez (2017, 2019) reconstruct FDI networks to identify firms' strategies in Italy and France, respectively, while De Masi and Ricchiuti (2018, 2020) extend their analysis to firms based in Europe.

De Masi and Ricchiuti (2020) reconstruct the development of the FDI network for the EU28 countries between 2003 and 2008. They link centrality measures obtained with macroeconomic variables to see if the way the network's architecture evolved could predict or follow changes in the of macroeconomic variables. Starting from their analysis, in this paper we use FDI outflow data to link production relationships between countries with their exposure to contagion. In our view, FDI naturally give rise to a network of reciprocal linkages and externalities (positive and/or negative) between a pair of countries, and these links could be a source of contagion. For example, when country A invests in country B, a series of transmission channels is triggered, primarily involving the transfer of machinery and equipment, and the movement of people. The greater a country's centrality in the global production network, the higher the likelihood of this country establishing a wide range of production linkages with other countries, raising its exposure to such transmission channels (Bonadio et al., 2020; Hwang, 2019; Sforza and Steininger, 2020).

We draw on data from fDi markets, a database administered by the Financial Times, which contains information on worldwide cross-border greenfield FDI projects. Our network topology measures are merged with publicly-available data on countries' COVID-19 infection and mortality rates, and other macroeconomic data considered as possible confounding factors. We find that, ceteris paribus, a greater centrality in the global FDI network coincides with higher infection and mortality rates in the EU28 countries. This result is robust to the use of alternative network topology measures, and the sensitivity of the FDI network to the business cycle. We also check whether this result is driven by the network dynamics of specific industries, and find that countries' exposure to the pandemic increases with their centrality in the following industry-specific FDI networks: business machinery and equipment, business services, finance, real estate, tourism and transport.

The rest of the paper develops as follows. Section 2 presents the data and the methods used to compute our network centrality measures (2.1), some descriptive statistics, and the econometric approach adopted (2.2). Section 3 presents the main results and robustness checks (3.1). Section 4 concludes.

2 Data and Method

Our empirical application refers to 27 European Union countries[1], for which we could combine three sources of data. One is the fDi Markets database administered by the Financial Times, which provides information on cross-border greenfield investment projects, covering all countries and sectors worldwide. From this database, we draw information on yearly outflows of greenfield FDI projects between 2003 and 2018. We use this dataset to compute the network centrality measures that we use as focal regressors in our econometric analysis, as described below. The second source is the European Centre for Disease Prevention and Control (ECDPC), which provides daily data on COVID-19 infections and deaths since the beginning of the coronavirus pandemic in February 2020. Country-level information is based on reports from health authorities around the world and updated every day by a team of epidemiologists. These data are validated by means of an epidemic intelligence process[2]. For our purposes, we select a period that spans from March 11^{th} to April 28^{th} 2020. We choose March 11^{th} as the starting date because by this was time all the 27 European countries considered had recorded at least one infection. We choose April 28^{th} as the end date to capture the first wave of SARS-Cov2 diffusion (which lasted approximately from early March to late April 2020). For our empirical analysis, we compute the rates of infection (INF/POP) and death (DEATH/POP), as the daily flows of infections and deaths, respectively, per million resident population in 2018. Figure 1 shows the daily evolution of these flows and the cumulative COVID-19 infections and deaths in our sample of countries.

Figure 1 about here.

The third source we use is the World Bank's platform of World Development Indicators, from which we draw data on several additional country-level variables potentially confounding the relationship between network centrality and the COVID-19 outbreak. The first of these variables is GDP per capita (GDPPC), in 2010 US dollars, that we use to capture the level of a country's wealth. The second is the share of resident population aged 65 years or more (POP65+). Third, we compute the import intensity of the country, as given by the value of imports on domestic GDP (IMPORT/GDP), to measure the contribution of merchandise trade inflows to the diffusion of the virus. In the same spirit, the fourth variable that we consider is the share of immigrants out of the total resident population (IMM/POP), which should capture the role of inflows of people as a potential carrier of SARS-Cov2. We also add the stock of public health facilities, given by the total number of hospital beds per capita (HBEDS/POP), including inpatient beds in public, private, general, and specialized hospitals and rehabilitation centers. Finally, we include the average temperature in February and March, expressed in degrees Fahrenheit (TEMP). All these control variables are measured in the latest year available, 2018. Table 1 shows their main summary statistics.

Table 1 about here.

2.1 Network and topology measurements

Network theory can shed light on links between entities (countries in our case) that traditional descriptive statistics do not capture. While a traditional analysis can clearly capture first-order measures, such as degree, other centrality measures (i.e. closeness, betweenness and eigenvector centrality) have no statistical equivalents in standard analyses. Hence our interest in enriching the analysis with elements derived from network theory.

Following De Masi and Ricchiuti (2020), we define an FDI network for each year from 2003 to 2018, and for each of the 38 sectors considered in the fDi Markets database. We obtain a graph comprising a set of nodes and links. In the present case, the nodes are EU27 countries. A link exists between country i and j if a firm based in i invests in j (i.e. it opens an affiliate[3]). Links are weighted, the weights being the number of affiliates opened in country j by firms based in i. Our original networks are therefore direct: each link has a direction associated with it.

Although FDI naturally creates a direct network (the firm in the investor country opens a subsidiary in the destination country), we do not see the role of the direction of this link as being uniquely determined. Indeed, the direction of contagion is clear in credit/debt networks, but for FDI this may not be true. Firms may decide to undertake FDI to expand into a stronger country or to cope with deteriorating economic conditions in the country of origin. That is why we symmetrize the adjacency matrix, transforming the direct network into an indirect one - as done for the construction of trade networks, which are similar to those of FDI (Fagiolo et al. 2013).

Constructing the network enables us to compute a series of centrality measures, and thereby identify the **core countries** in the network. It is worth noting that the notion of hub crucially depends on a network's topological characteristics and specificity. Different measures of centrality have been designed precisely to capture distinct aspects of the concept of a node's centrality. Though these measures are correlated, they may identify different countries as hubs (Krackhardt, 1990). We calculate both local (degree of centrality, average degree of neighbors, clustering and squared clustering) and higher-order measures (betweenness, closeness, eigenvector centrality, eccentricity).

Degree is a simple measure for identifying a hub. It is given by the number of links that each node has. Starting from the concept of degree, we can identify a hub in the network by calculating **the average neighbor degree** (Ave Neigh Degree), which generally depends on the degree of the node considered (Caldarelli, 2007). Having a high *average* means that the country is linked to highly-connected countries. This indicator can also help us to see if a network is assortative, i.e. if the nodes are similar in some way. To be more specific, if the average degree of the neighbors increases with the node's degree, then the network is assortative; if it decreases, then the network is disassortative.

Another local measure we consider is the **clustering coefficient** (CLUSTERING), which is a measure of the density of connections around a vertex. It enables us to calculate the proportion of the neighbors closest to the node that are connected to one another. In our opinion, a greater clustering lead to an easier transmission of a shock, or a virus, between 'neighboring' countries.

We also consider **squared clustering** (CLUSTERING2), which is the density of squared around the node. This measure captures the connections of the prime nodes that are neighbors of the node being analyzed. A higher squared clustering coefficient means that the nodes are very connected to each other through another (common) node. The concept of density is reinforced and increases the possibility of contagion between the node and its neighbors.

The centrality measures discussed so far are local: they concern the specifics of the node and its neighbors. The other measures taken into consideration are global: although they are calculated for each node, their value depends on the structure of the network as a whole.

A classic global measure is **betweenness** (Brandes, 2001). This is given by the number of times a node k is crossed by two other nodes (i and j) to minimize the length of the path between the two (from i to j).

This measure is meaningful when we examine networks that concern flows of information or goods. For our purposes, it is relevant because we expect countries with a greater betweenness to have seen a greater increase in infections, precisely because the flows pass primarily through them.

Another measure that we employ is **closeness centrality** (see Freeman, 1977 and Sabidussi, 1966), which is the reciprocal of the average distance of one node from the others. Countries with a higher closeness centrality are those lying closer to all the others, and therefore where infections are transmitted more quickly.

The last two measures that we consider are **eccentricity** and **eigenvector centrality** (Newman, 2010). The former is the maximum distance of a node from any other node, and it is calculated using the following formula:

$$e_i = \max_{\forall j \in N} d_{ij} \tag{1}$$

A lower e_i the higher is the countries' centrality. The latter, eigenvector centrality, has to do not with the distance between nodes, but with the neighbors' centrality, in a recursive way. To be specific, using matrix notation, the eigenvector centrality of a node i is:

$$c_i = \frac{1}{\lambda} \sum_j W_{ij} c_j \tag{2}$$

where λ is the largest eigenvalue. A higher score implies that the node (i.e. the country) is connected to many nodes that themselves have high eigenvector centrality scores. It is worth noting that these global measures cannot be reduced to traditional statistical measurements, and this goes to show the greater explanatory power of network theory.

As mentioned earlier, the networks (and therefore the centrality measures) have been built at sector level. For our purposes, we aggregate each of the above measures using as a weight the number of affiliates for each single sector. The formula is as follows:

$$NC_{it} = \frac{1}{N} \sum \gamma_{ijt} NC_{ijt} \tag{3}$$

where NC is one of the above-mentioned indexes, N is the number of sectors, and γ_{ijt} is, for each country i, the ratio of the number of affiliates in sector j to the total number in the year t, while NC_{ijt} is the NC of sector j of country i in the year t.

Our final network centrality (NC) indicators are the average of each NC_{it} across the years 2003-2018. We thus obtain a measure of the average centrality of a country in the long run.

The maps in Figure 2 show the average of some of our centrality indexes[4]. All the pictures are fairly consistent: there is a core (UK, France, Germany and, to lesser extent, Italy and Spain), and a clearly-distinguishable periphery. The clustering, on the other hand, is less clear-cut, but consistent with the other maps: countries with the highest clustering have 'neighbors' with higher degrees of centrality.

Figure 2 about here

Figures 3 and 4 show how our local (panels A) and global (panels B) NC measures correlate with INF/POP and DEATH/POP, respectively.

The four panels show very similar correlations. Panel A in each figure shows that both INF/POP and DEATH/POP correlate positively (and significantly) with three out of four NC indexes, namely DEGREE, CLUSTERING and CLUSTERING2, whereas the correlation with AVE NEIGH DEGREE is negative. Analyzing the network, we note that it is disassortative: nodes with a large DEGREE are connected with nodes that have smaller average degrees. In other words, the smaller the AVE NEIGH DEGREE, the greater the degree of the analyzed node, and the greater the number of deaths or infections. The trend of this variable is therefore also consistent with that of the others.

Figure 3 about here

Figure 4 about here

The two panels B confirm that both the infection rate and the death rate increase with the centrality of the country in the global FDI network, judging from the positive correlation with the BETWEENNESS, CLOSENESS and EIGENVECTOR centrality measures, and the negative correlation with ECCENTRICITY.

We now test whether these correlations are robust to the inclusion of additional confounding factors and across different periods.

2.2 Econometric Approach

To test our hypothesis, we estimate the following equation:

$$ln(Y)_{it} = \beta_0 + \beta_1 lnNC_{it0} + \beta_k Z_{kit0} + \delta_t + \epsilon_{it} \quad (4)$$

where Y is either the number of people infected with COVID-19 per million population (i.e. the infection rate, INF/POP) of country i on day t, or, alternatively, the number of deaths per million population (i.e. the mortality rate, DEATH/POP) of country i on day t. These two dependent variables are regressed against a constant term β_0, our focal regressors of network centrality (NC), a vector **Z** of additional control variables, a series of day-specific dummies δ_t that control for the time trend of the pandemic in March and April, and a stochastic error term ϵ_{it}.

As network centrality measures (NC), we consider two pairs of the four measures mentioned in section 2.1: two local (DEGREE and CLUSTERING), and two global (BETWEENNESS and EIGENVECTOR). Among the additional regressors in **Z** we include: the level of GDP per capita (GDPPC); the share of the population aged 65 or more (POP65+); the import intensity of the country (IMP/GDP), given by the value of total imports out of the GDP; the immigration rate (IMM/POP), computed as the number of immigrants out of the total resident population; the number of hospital beds per capita (HOSP/POP), which includes inpatient beds in public, private, general, specialized hospitals and rehabilitation centers; and the average temperature in February and March, expressed in degrees Fahrenheit (TEMP). All these variables are transformed into natural logarithms so that their estimated coefficients can be interpreted as semi-elasticities. Table 2 shows the matrix of pairwise correlations between our regressors.

Table 2 about here

Our two dependent variables, INF/POP and DEATH/POP, vary on a daily basis, whereas NC and all the variables in **Z** are time-invariant regressors observed in the year 2018. To be more precise, NC is computed as the average network centrality of a country between 2003 and 2018, while all the other variables are measured in 2018. We consequently cannot estimate our two equations using a fixed effect estimator, so we use a random effects estimator, with standard errors clustered at country level. Based on our expectations, the coefficient β_1 should be positive **(with the exception of AVE NEIGH DEGREE and ECCENTRICITY)** and statistically significant. This means that, ceteris paribus, the infection (and mortality) rate increases as a country's position in the global production network becomes more central.

To test the robustness of our results, we run a series of additional estimates. First, we test for sensitivity to alternative measures of network centrality. We calculate our two equations again, one for the infection rate and one for the mortality rate, replacing the previous four indicators with: average neighbor degree and squared clustering as local measures of NC; and closeness centrality and eccentricity as global measures of NC. As a second robustness test, we check whether the results might be affected by endogeneity. Although the structure of the global production network precedes the COVID-19 outbreak, we can assume that a global negative shock in the past could lead firms to (re)organize their value chains in order to mitigate, or unwittingly exacerbate, the transmission of possible future shocks. In this respect, one of the most plausible scenarios is offered by the global financial crises in 2008-09 and 2011-12. In response to the two downturns, multinational enterprises could have presumably reduced the geographical scope of their foreign investment flows, or (re)directed them towards areas less exposed to the financial contagion, thereby reshaping their global network and adopting a more central or a more peripheral position. To check for the sensitivity of our results to the business cycle, we compute the average scores for NC in two different periods, before (2003-08) and after the global financial crises (2013-2018), and we use them to replace the original NC variables in Equation 4.

Then we test whether the relationship between country network centrality and SARS-Cov2 infection and mortality rates is determined by specific sector dynamics, i.e. by the concentration of greenfield FDI in some specific industries in a country. To do so, we recompute our average network centrality measures for the 34 sectors of economic activity in which foreign investors operate (see the Appendix, Table A1 for the full list), and we calculate Equation 4 again, sector by sector.

3 Results

As network centrality measures, we consider two pairs of the four indicators mentioned in section 2.1: two local, degree and clustering; and two global, betweenness and eigenvector centrality.

Tables 3 and 4 show the random effects panel data estimates for INF/POP and DEATH/POP, respectively. Table 3, Column 1, shows that, ceteris paribus, the infection rate rises significantly as the DEGREE of the country in the global production network increases. Columns 2 and 4 confirm this result for CLUSTERING and EIGENVECTOR centrality, whereas the estimated coefficient of BETWEENNESS in Column 3 is positive but not statistically significant. Among the other regressors, we find that the COVID-19 infection rate changes with a country's level of GDP per capita, share of elderly in the population, endowment of hospital beds per capita, and temperature in February-March.

Table 3 about here

We also find that the within R^2 value is much lower than the between R^2 or overall R^2, indicating that it is appropriate to use a random effects estimator. The mean and maximum VIF statistics also confirm that multicollinearity is not an issue, as they are well below the commonly-accepted threshold of 5. Interestingly, the AIC and BIC statistics show that the model that better fits the data is the one in Column 1, where network centrality is captured through the DEGREE indicator. In this case, we find that an increase of one standard deviation in the degree (which means passing from the position of Slovenia in the 25th percentile to the position of Belgium, or Sweden, in the 75th percentile) corresponds to an average 0.55% increase in the infection rate. The corresponding average marginal effect for EIGENVECTOR is 0.46%.

Table 4 confirms that a greater centrality in the global production network coincides with a higher mortality rate: in all four columns, the estimated coefficients of the network centrality indicators are positive and statistically significant. In this case, the AIC and BIC statistics show that the model best fitting the data is the one in Column 4, where EIGENVECTOR is used as the focal regressor. Here we find that a one standard deviation increase in eigenvector centrality coincides with an average 0.6% increase in the mortality rate. It is worth noting that, compared with the other variables, the average marginal effect (AME) of network centrality is almost always the highest. According to our estimates, the topology of the FDI network significantly affects both the infection and the mortality rate. These latter increase the higher the links of a country (DEGREE), the density of its contacts (CLUSTERING),its centrality in the network (BETWEENNESS) and the stronger its connection with other well-connected countries (EIGENVECTOR).

Table 5 shows the AME of DEGREE and EIGENVECTOR, derived from the estimates in Tables 3 and 4, Columns 1 and 4, respectively. In almost all cases, we find that a country's network centrality is the variable that most affects COVID-19 pandemic outcomes, with a marginal effect that exceeds that of GDP per capita or number of hospital beds.

Table 4 about here

Table 5 about here

3.1 Robustness Tests

We run a set of robustness checks to see whether our results: (a) are sensitive to alternative local and global measures of network centrality; (b) are sensitive to the business cycle; and/or (c) depend on the network dynamics of specific sectors. As concerns (a), we re-calculate Equation 4 using the following alternative pairs of indicators of NC: average neighbor degree and clustering2 as local measures, closeness centrality and eccentricity as global measures. Tables 6 and 7 show the corresponding random effects panel data estimates for INF/POP and DEATH/POP, respectively.

In Table 6 three out of four measures of NC show a weak statistical significance, namely CLUSTERING2, CLOSENESS, and ECCENTRICITY, whereas the estimated coefficient of AVERAGE NEIGHBOR DEGREE is not statistically significant. The AIC and BIC statistics show, however, that using these alternative indicators does not improve on the goodness of fit obtained with the models in Table 3. From Table 7, on the other hand, we find only two out of four indicators of NC statistically significant in explaining the dynamics of the mortality rate: closeness centrality and eccentricity. Again, the AIC and BIC statistics show that using these alternative indicators does not improve the goodness of fit vis-à-vis the models estimated in Table 4. We conclude that our results are robust to alternative measurements of network centrality.

Concerning item (b), we re-compute our NC variables in two sub-periods: 2003-2008 (before the 2008-09 and 2011-12 financial crises) and 2013-2018 (afterwards). Then we calculate Equation 4 again using these two alternative sets of NC indicators, and we check whether their estimated coefficients vary in the two different phases of the business cycle. Tables 8 and 9 show the results of the panel data estimates. Table 8 refers to the INF/POP and DEATH/POP equations where NC is measured in 2003-08, Table 9 to the cases where it is measured in 2013-18. For reasons of space, we only report the estimated coefficients of the NC variables. The estimates confirm that the main results in Tables 3 and 4 do not change if we measure a country's position in global production networks before and after the financial crises. In short, the relationship between network centrality and COVID-19 infection or mortality rates does not seem to be affected by the sensitivity of network topologies to the business cycle.

Table 6 about here

Table 7 about here

To address item (c), we first consider the four network centrality measures at (two-digit) sector level (as described in Section 2.2), then we calculate Equation 4 separately for each of the 34 sectors in our dataset. We take all the estimated coefficients for each of the four NC measures and plot them in two separate graphs, one for INF/POP and one for DEATH/POP. Figures 5 and 6 show the coefficients estimated for the impact of EIGENVECTOR on the infection rate and mortality rate, respectively. In both figures, we only show the sectors for which the estimated EIGENVECTOR coefficient is statistically significant (figures showing the elasticities of all the other NC measures are in the Appendix, Figures A1-A4).

We find that sectors with the highest (positive) elasticities are biotechnologies, business machinery and equipment (including computers), business services, coal, engines and turbine production, financial services, plastics manufacturing, software, tourism and transport. Intriguingly, the highest estimated coefficient in both cases is for the business machinery sector. Many of the industries in this sector are characterized by an intensive use of intermediate inputs, which means that their global production network is particularly dense. Be that as it may, we conclude that our main results are not driven by the dynamics of a restricted group of sectors.

Table 8 about here

Table 9 about here

Figure 5 about here

Figure 6 about here

4 Discussion and Conclusions

Does being at the center of a global production network make a country more vulnerable to the COVID-19 pandemic? In this paper, we try to answer this question by focusing on EU27 countries and merging data from different sources on daily COVID-19 infection and mortality rates in March and April 2020, on countries? greenfield FDI projects between 2003 and 2018, and on other macroeconomic variables in 2018. Our random effects panel data estimates show that, ceteris paribus, a country's greater centrality in the global production network coincides with higher chances of its people becoming infected and killed by the coronavirus. These results are robust to the use of alternative network centrality indicators and to the dynamics of the business cycle. We also find that this relationship is not driven by the network dynamics of a single sector, or handful of sectors. It affects many industries in the EU, and especially the business machinery and equipment, business services, real estate, textiles, tourism and transport sectors. We also find that the average marginal effects of the relevant network centrality measures are the highest among those of all the regressors, implying that the structure of the production network is a crucial element to consider when explaining the initial dynamics of the COVID-19 pandemic. The picture that emerges from our analysis is one where the outbreak originated in China, then spread to Europe, hitting countries that are hubs of the global production network particularly hard, regardless of their wealth, trade openness, immigration rate, or health facilities. Our findings complement other recent evidence concerning globalization and the COVID-19 pandemic. They may be useful for illustrating the role of global value chains, and of the underlying production network, in explaining the magnitude of the economic effects of the pandemic (Sforza and Steininger, 2020). In this paper, we do not directly investigate the mechanisms by which the coronavirus has spread across countries and regions. Instead, we provide evidence of the importance of inter- and intra-sector production linkages in its diffusion.

Notes

[1]Excluding Luxembourg because it is an outlier as regards inward FDI
[2]For more details, see: https://www.ecdc.europa.eu/en/covid-19/data-collection.
[3]the fDi markets database refers to projects, but we prefer to use the term affiliates.
[4]The maps for the other indicators not included here are available on request.

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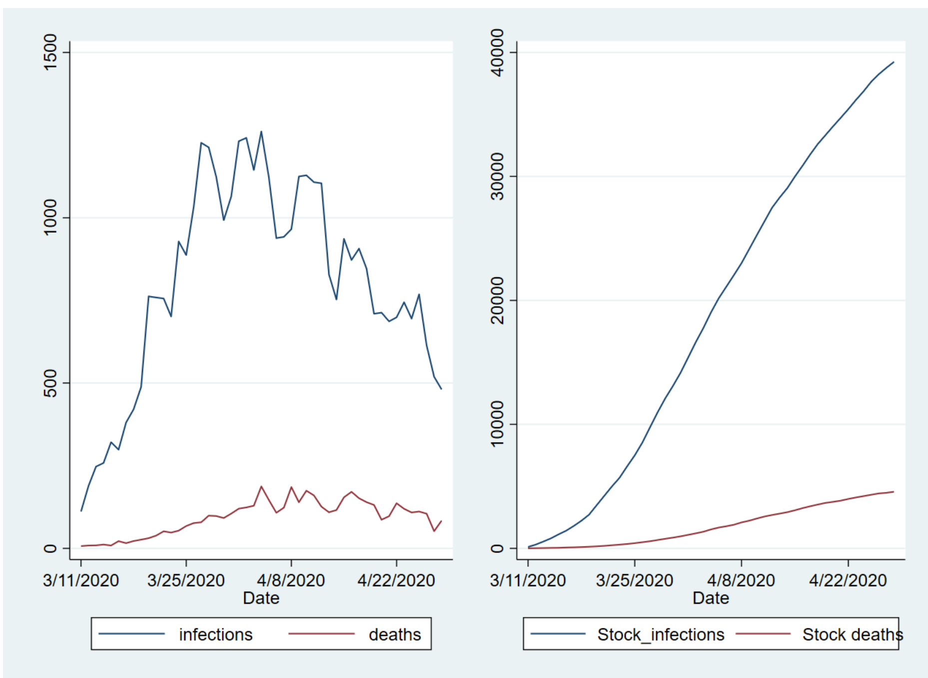
Table 1: Summary statistics

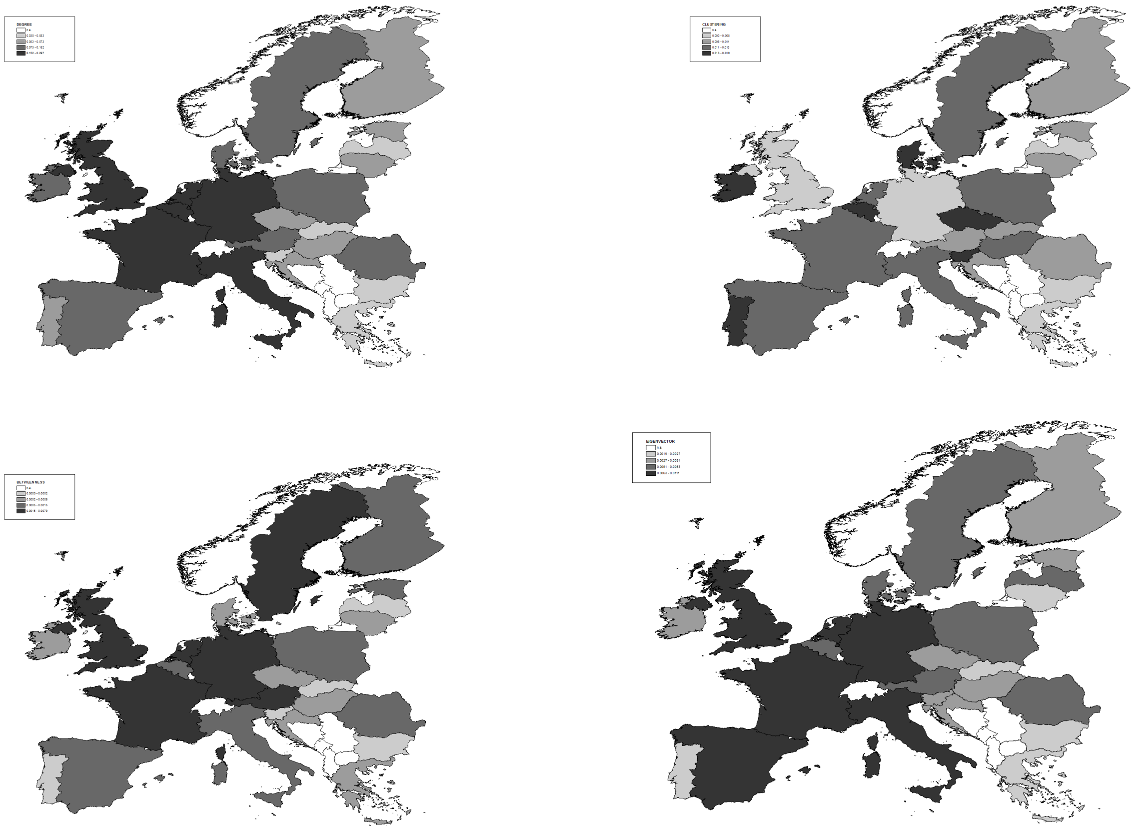
Variable	Mean	Std.dev.	Min	Max
INF/POP	31.10	36.58	0.091	259.5
DEATHS/POP	2.818	5.293	0	51.94
GDPPC	29845.7	15826.6	6846.08	59669.9
POP 65+	0.170	0.022	0.116	0.208
IMPORT/GDP	0.549	0.232	0.263	1.355
IMM/POP	0.012	0.011	0.001	0.062
HBEDS/POP	4878.28	1714.47	2300.08	8079.50
TEMP (Feb-Mar, °F)	36.12	8.383	16.59	53.65

Figure 1: Evolution of the pandemic in the EU27 countries



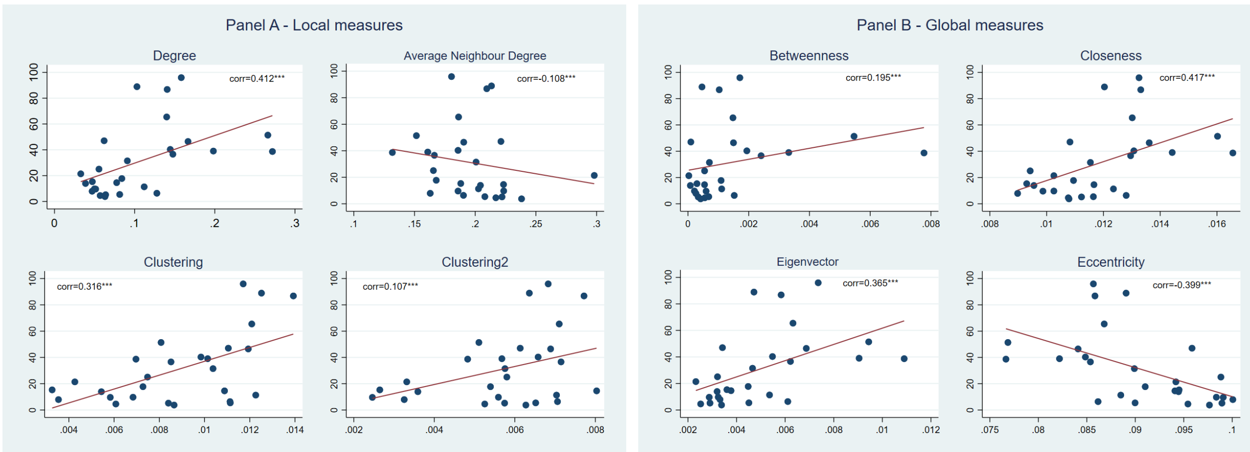
Source: authors' elaborations on ECDPC data.

Figure 2: Maps of Some Measures at 2018



Source: authors’ elaborations

Figure 3: Scatter plot for INF/POP and local versus global centrality measures



Source: authors' elaborations

Figure 4: Scatter plot for DEATHS/POP and centrality measures

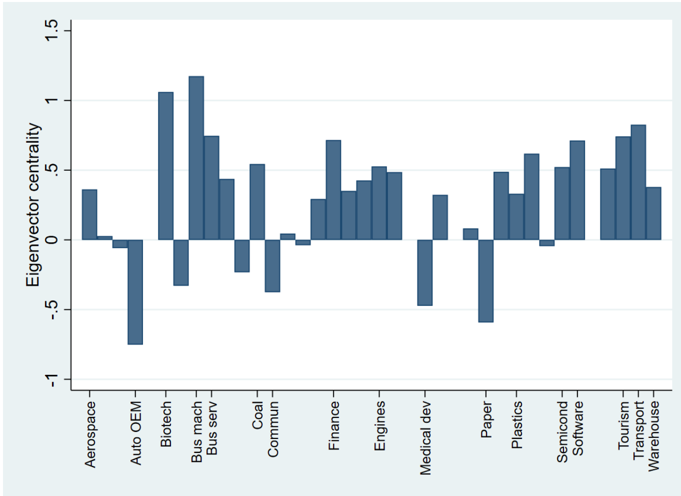
Source: authors' elaborations

Table 2: Correlation matrix

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Degree	1													
2. Ave Neigh Degree	-0.56*	1												
3. CLUS	0.43*	0.11*	1											
4. CLUS2	0.28*	0.08*	0.87*	1										
5. BETW	0.88*	-0.73*	0.26*	0.17*	1									
6. CLOSE	0.85*	-0.06°	0.45*	0.29*	0.64*	1								
7. EIGEN	0.88*	-0.68*	0.28*	0.15*	0.82*	0.60*	1							
8. ECC	-0.72*	0.35*	-0.27*	-0.21*	-0.51*	-0.63*	-0.78*	1						
9. GDPPC	0.55*	-0.20*	0.25*	0.12*	0.37*	0.52*	0.46*	-0.63*	1					
10. POP65	0.19*	-0.10*	-0.05°	0.07°	0.24*	0.23*	0.19*	-0.39*	0.01	1				
11. IMP	-0.55*	0.47*	-0.16*	-0.07*	-0.64*	-0.39*	-0.50*	0.42*	-0.24*	-0.48*	1			
12. IMM	-0.02	0.10*	-0.16*	-0.12*	-0.14*	-0.08*	-0.02	-0.18*	0.38*	-0.09*	0.30*	1		
13. HBED	-0.10*	0.06°	-0.09*	0.09*	0.03	-0.03	-0.07*	0.25*	-0.54*	0.11*	0.24*	-0.29*	1	
14. TEMP	0.08*	0.21*	0.01	0.03	-0.14*	0.19*	-0.06°	0.02	0.00	-0.20*	-0.03	0.16*	-0.06°	1

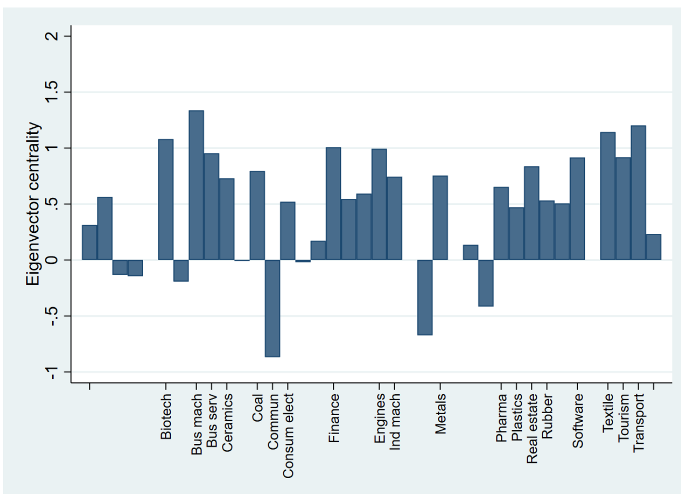
Notes: All variables are transformed in natural logarithm. * significamt at 1% level; ° significant at 5% level

Figure 5: Estimated coefficients of EIGENVECTOR for different sectors, INF/POP



Source: authors' elaborations

Figure 6: Estimated coefficients of EIGENVECTOR for different sectors, DEATH/POP



Source: authors' elaborations

Table 3: INF/POP

Dep. Var. INF/POP	(1)	(2)	(3)	(4)
DEGREE	0.922**			
	(0.365)			
CLUSTERING		0.637**		
		(0.313)		
BETWEENNESS			247	
			(0.165)	
EIGENVECTOR				0.987**
				(0.407)
GDPPC	0.578**	0.961***	0.940***	0.776***
	(0.237)	(0.179)	(0.221)	(0.214)
POP65+	1.560**	1.335**	1.622*	1.568**
	(0.683)	(0.658)	(0.882)	(0.770)
IMP/GDP	0.672	-0.062	0.525	0.556
	(0.505)	(0.348)	(0.647)	(0.464)
IMM/POP	0.131	0.259*	0.091	0.92
	(0.146)	(0.145)	(0.189)	(0.161)
HOSP/POP	-0.781**	-0.255	-0.607*	-0.641*
	(0.354)	(0.218)	(0.311)	(0.330)
TEMP	0.488	0.581	0.856**	0.798**
	(0.375)	(0.364)	(0.354)	(0.353)
Day dummies	Yes	Yes	Yes	Yes
Constant	8.385	0.206	1.346	6.955
	(6.367)	(4.162)	(5.556)	(6.413)
N	1323	1323	1323	1323
R^2 within	0.173	0.173	0.173	0.173
R^2 between	0.776	0.725	0.686	0.766
R^2 overall	0.490	0.464	0.443	0.485
Mean VIF	2.42	2.34	2.47	2.38
Max VIF	2.79	2.88	3.91	2.88
AIC	3816.6	3884.4	3934.1	3831.2
BIC	4013.7	4081.5	4131.2	4028.3

Notes: country-level cluster-robust standard errors in parentheses. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table 4: DEATH/POP

Dep. Var. DEATH/POP	(1)	(2)	(3)	(4)
DEGREE	1.146***			
	(0.390)			
CLUSTERING		1.019**		
		(0.491)		
BETWEENNESS			0.391**	
			(0.199)	
EIGENVECTOR				1.366***
				(0.397)
GDPPC	0.321	0.834***	0.684**	0.440*
	(0.291)	(0.259)	(0.312)	(0.257)
POP65+	2.144**	1.738	1.91	2.314**
	(1.087)	(1.141)	(1.193)	(1.094)
IMP/GDP	0.951	-0.124	0.935	0.972*
	(0.636)	(0.511)	(0.814)	(0.559)
IMM/POP	0.045	0.28	-0.056	0.031
	(0.273)	(0.271)	(0.364)	(0.247)
HOSP/POP	-1.293***	-0.572	-1.292***	-1.312***
	(0.482)	(0.372)	(0.503)	(0.472)
TEMP	1.046***	1.192***	1.637***	1.371***
	(0.370)	(0.426)	(0.378)	(0.315)
Day dummies	Yes	Yes	Yes	Yes
Constant	11.77	1.545	5.197	14.19**
	(7.404)	(5.439)	(7.480)	(6.412)
N	924	924	924	924
R^2 within	0.065	0.065	0.065	0.066
R^2 between	0.733	0.596	0.619	0.734
R^2 overall	0.398	0.363	0.35	0.401
Mean VIF	2.26	2.2	2.29	2.25
Max VIF	2.99	2.99	3.06	2.99
AIC	3061.3	3113.9	3132.2	3057.3
BIC	3244.8	3297.5	3315.7	3240.8

Notes: country-level cluster-robust standard errors in parenthesis. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table 5: Average Marginal Effects

Variable	INF/POP (Table 3)		DEATH/POP (Table 4)	
DEGREE	0.548**		0.635***	
EIGENVECTOR		0.455**		0.602***
GDPPC	0.349**	0.468***	0.192	0.263*
POP65+	0.225**	0.226**	0.281**	0.303**
HOSP/POP	-0.293**	-0.240*	-0.511***	-0.519***
TEMP	128	0.209**	0.266***	0.349***

Notes: values in cells refer to the average marginal effect of a one standard deviation increase in each variable

Table 6: Robustness INF/POP

Dep. Var. INF/POP	(1)	(2)	(3)	(4)
AVERAGE NEIGHBOUR DEGREE	-0.493			
	(0.520)			
CLUSTERING2		0.438*		
		(0.243)		
CLOSENESS			1.828*	
			(1.028)	
ECCENTRICITY				-4.033*
				(2.074)
GDPPC	1.125***	1.050***	0.789***	0.772***
	(0.215)	(0.208)	(0.246)	(0.266)
POP65+	1.403	1.043	0.951	0.391
	(0.924)	(0.783)	(0.846)	(1.027)
IMP/GDP	0.139	-0.113	0.143	0.063
	(0.554)	(0.381)	(0.432)	(0.417)
IMM/POP	0.103	0.19	0.132	0.108
	(0.190)	(0.159)	(0.171)	(0.169)
HOSP/POP	-0.288	-0.305	-0.560**	-0.319
	(0.265)	(0.232)	(0.277)	(0.250)
TEMP	0.771**	0.56	0.363	0.589
	(0.398)	(0.415)	(0.478)	(0.433)
Day dummies	Yes	Yes	Yes	Yes
Constant	-6.096	-1.85	9.276	-12.45**
	(3.628)	(4.412)	(8.486)	(5.296)
N	1323	1323	1323	1323
R^2 within	0.173	0.173	0.173	0.173
R^2 between	0.665	0.688	0.704	0.71
R^2 overall	0.432	0.444	0.452	0.456
Mean VIF	2.37	2.33	2.4	2.39
Max VIF	2.88	2.88	2.88	2.88
AIC	3960	3931.6	3911.6	3903.5
BIC	4157.2	4128.7	4108.7	4100.7

Notes: country-level cluster-robust standard errors in parenthesis. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table 7: Robustness DEATH/POP

Dep. Var. DEATH/POP	(1)	(2)	(3)	(4)
AVERAGE NEIGHBOUR DEGREE	-1.034			
	(0.908)			
CLUSTERING2		0.533		
		(0.375)		
CLOSENESS			2.861*	
			(1.480)	
ECCENTRICITY				-5.680**
				(2.711)
GDPPC	0.906***	0.946***	0.494	0.449
	(0.330)	(0.330)	(0.331)	(0.354)
POP65+	1.63	1.258	1.43	0.734
	(1.235)	(1.220)	(1.202)	(1.274)
IMP/GDP	0.475	-0.087	0.532	0.398
	(0.578)	(0.586)	(0.644)	(0.621)
IMM/POP	-0.007	0.152	0.16	0.114
	(0.395)	(0.327)	(0.315)	(0.290)
HOSP/POP	-0.941**	-0.721*	-1.092**	-0.837*
	(0.459)	(0.395)	(0.465)	(0.473)
TEMP	1.549***	1.210**	0.964*	1.143**
	(0.431)	(0.496)	(0.518)	(0.465)
Day dummies	Yes	Yes	Yes	Yes
Constant	-4.754	-1.843	17.56	-12.8
	(7.035)	(6.656)	(11.13)	(8.857)
N	924	924	924	924
R^2 within	0.064	0.065	0.065	0.065
R^2 between	0.58	0.579	0.64	0.681
R^2 overall	0.331	0.33	0.357	0.361
Mean VIF	2.24	2.2	2.26	2.25
Max VIF	2.99	2.99	2.99	2.99
AIC	3159.3	3159.7	3122.4	3116.2
BIC	3342.8	3343.2	3305.9	3299.7

Notes: country-level cluster-robust standard errors in parenthesis. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table 8: Robustness 2003-2008

panel A - Dep. Var. INF RATE	(1)	(2)	(3)	(4)
DEGREE2003-08	0.649**			
	(0.315)			
CLUSTERING2003-08		0.249**		
		(0.104)		
BETWEENNESS2003-08			0.146	
			(0.124)	
EIGENVECTOR2003-08				1.067**
				(0.519)
Control variables	Yes	Yes	Yes	Yes
Day dummies	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
N	1323	1323	1323	1323
R^2 within	0.173	0.173	0.173	0.173
R^2 between	0.705	0.687	0.67	0.743
R^2 overall	0.453	0.443	0.434	0.473
Panel B - Dep. Var. DEATH RATE				
DEGREE2003-08	0.999***			
	(0.379)			
CLUSTERING2003-08		0.378**		
		(0.165)		
BETWEENNESS2003-08			0.343***	
			(0.131)	
EIGENVECTOR2003-08				1.579***
				(0.509)
Control variables	Yes	Yes	Yes	Yes
Day dummies	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
N	1323	1323	1323	1323
R^2 within	0.065	0.065	0.065	0.065
R^2 between	0.666	0.576	0.639	0.708
R^2 overall	0.366	0.333	0.353	0.394

Notes: country-level cluster-robust standard errors in parenthesis. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

Table 9: Robustness 2013-2018

panel A - Dep. Var. INF RATE	(1)	(2)	(3)	(4)
DEGREE2013-18	0.472***			
	(0.315)			
CLUSTERING2013-18		0.242*		
		(0.143)		
BETWEENNESS2013-18			0.246*	
			(0.144)	
EIGENVECTOR2013-18				0.362**
				(0.162)
Control variables	Yes	Yes	Yes	Yes
Day dummies	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
N	1323	1323	1323	1323
R^2 within	0.173	0.173	0.173	0.173
R^2 between	0.772	0.701	0.713	0.75
R^2 overall	0.488	0.451	0.457	0.478
Panel B - Dep. Var. DEATH RATE				
DEGREE2013-18	0.645***			
	(0.201)			
CLUSTERING2013-18		0.386*		
		(0.234)		
BETWEENNESS2013-18			0.239	
			(0.173)	
EIGENVECTOR2013-18				0.528***
				(0.173)
Control variables	Yes	Yes	Yes	Yes
Day dummies	Yes	Yes	Yes	Yes
Constant	Yes	Yes	Yes	Yes
N	1323	1323	1323	1323
R^2 within	0.065	0.065	0.065	0.065
R^2 between	0.716	0.576	0.634	0.708
R^2 overall	0.399	0.346	0.345	0.393

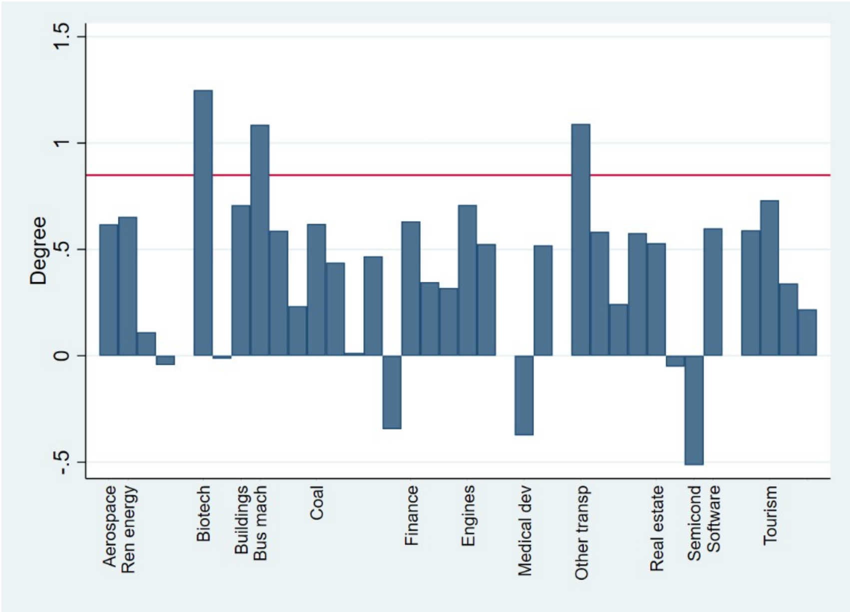
Notes: country-level cluster-robust standard errors in parenthesis. *** significant at 1% level; ** significant at 5% level; * significant at 10% level.

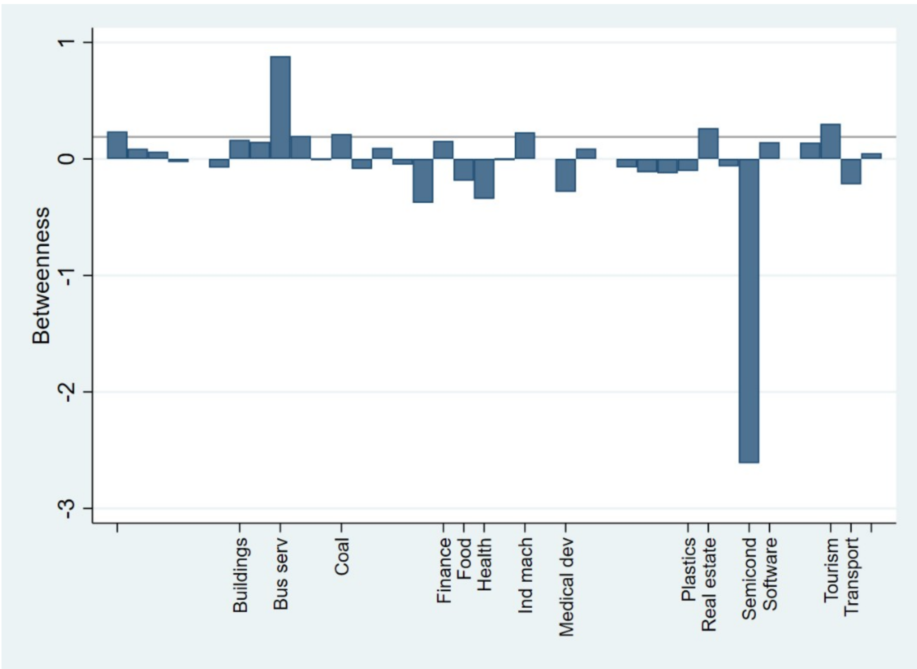
Appendix

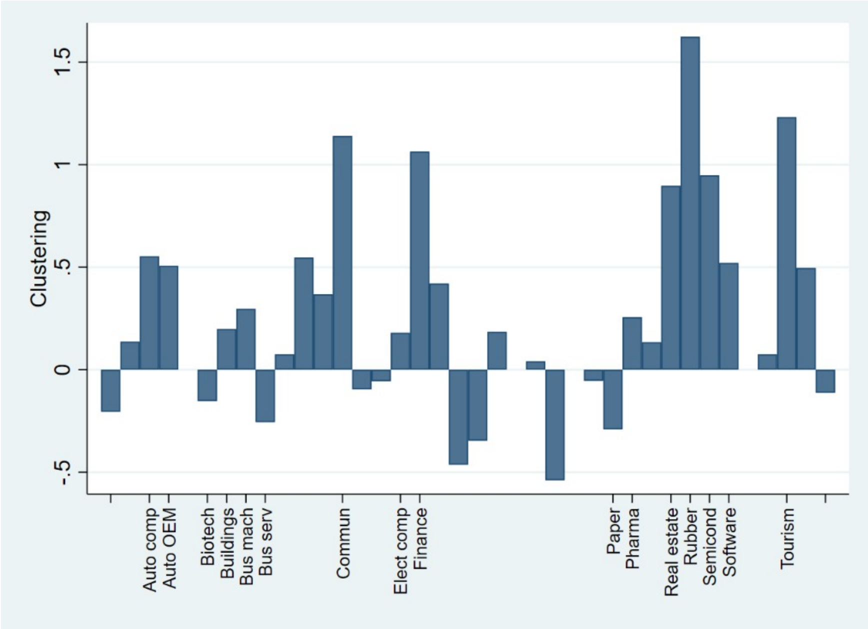
Table A1. List of sectors

Sector	SIC code
Aerospace	372
Alternative/Renewable energy	2819, 2869
Automotive Components	3714
Automotive OEM	3711, 3713, 551, 552, 553, 75
Beverages	208
Biotechnology	2836, 8731
Building & Construction Materials	17, 324, 327, 5032, 5033, 5039, 5211
Business Machines & Equipment	357
Business Services	731, 732, 733, 734, 735, 736, 738, 81, 82, 871, 872, 8732, 8733, 874
Ceramics & Glass	321, 322, 323, 325, 326, 328, 329
Chemicals	281, 2833, 284, 285, 286, 287, 289, 8731
Coal, Oil & Gas	12, 13, 29, 554
Communications	366, 482, 483, 484, 489
Consumer Electronics	363, 365, 386
Consumer Products	387, 391, 393, 394, 395, 396, 399, 523, 525, 526, 527, 53?, 563, 569, 57, 59, 76
Electronic Components	362, 364, 3671, 3672, 3677, 3678, 3679, 369
Financial Services	60, 61, 62, 63, 64, 67
Food & Tobacco	01, 02, 07, 08, 09, 201, 202, 203, 204, 205, 206, 207, 209, 21, 54
Healthcare	80, 83
Engines & Turbines	351?
Industrial Machinery, Equipment & Tools	352, 353, 354, 355, 356, 358, 359, 361?, 382
Leisure & Entertainment	58, 78, 79, 84
Medical Devices	384, 385
Metals	10, 33, 34
Minerals	14
Non-Automotive Transport OEM	373, 374, 375, 379, 3715, 3716, 555, 556, 557, 558, 559
Paper, Printing & Packaging	26, 27
Pharmaceuticals	2834, 2835, 8731, 8734
Plastics	282
Real Estate	15, 16, 65
Rubber	30
Semiconductors	3674, 3675, 3676
Software & IT services	737
Space & Defence	376, 3812
Textiles	22, 23, 31, 561, 562, 564, 565, 566
Hotels & Tourism	70
Transportation	40, 41, 43, 44, 45, 46, 47, 49?, 4212, 4213, 4215
Warehousing & Storage	4214, 422, 423
Wood Products	24, 25?

Figure A1 – Estimated coefficients of other NC measures for different sectors, INF/POP







Clustering
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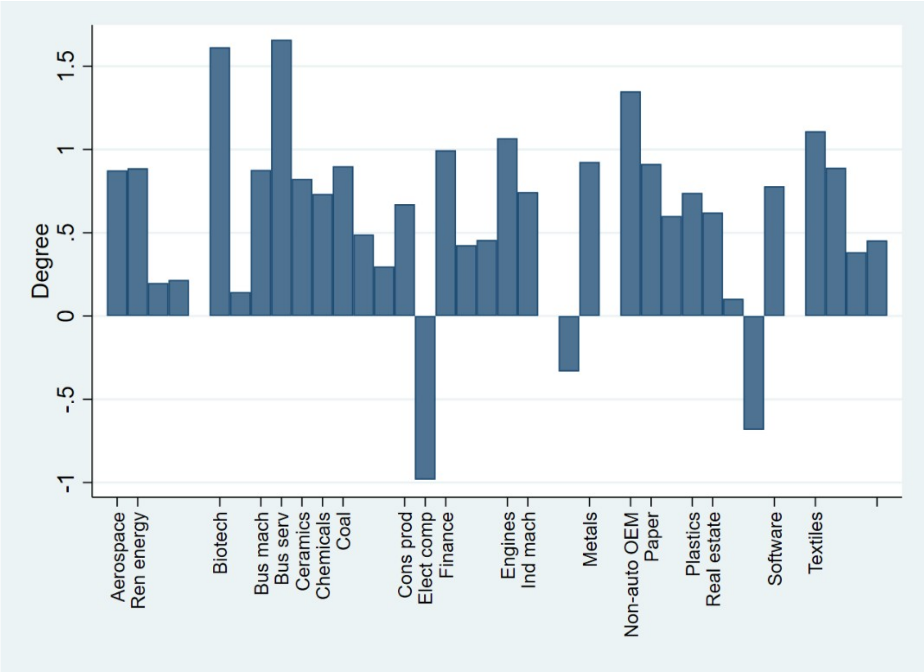
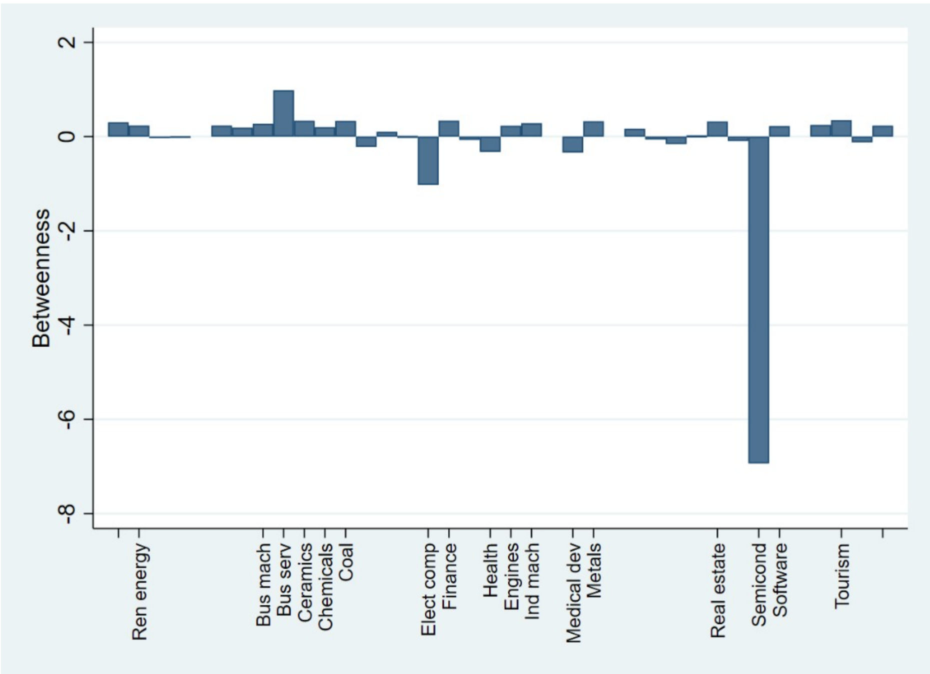
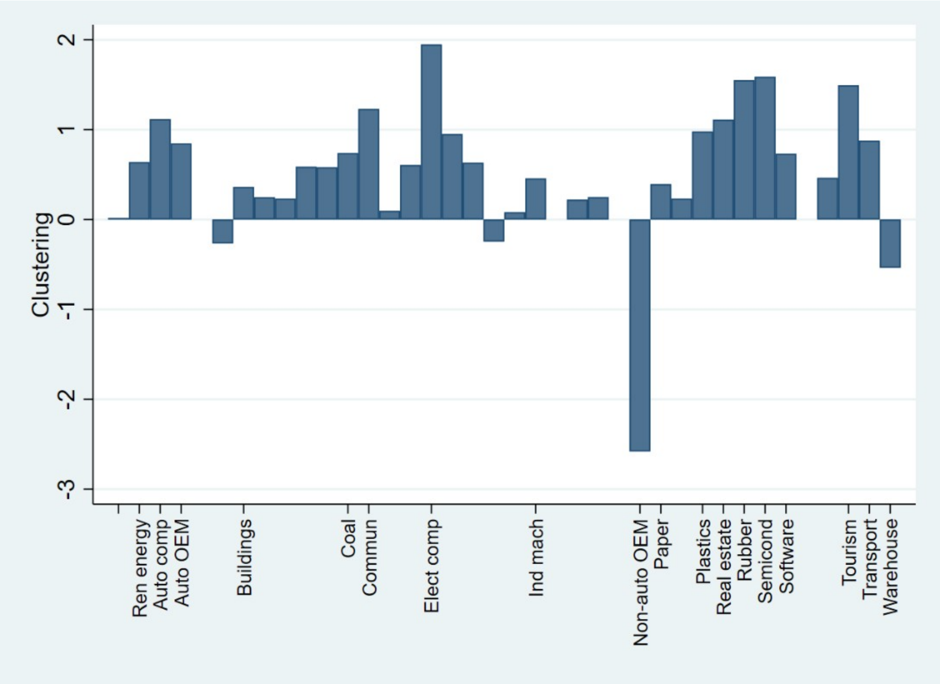
1.5
Auto comp
Auto OEM
Biotech
Buildings
Bus mach
Bus serv
Commun
Elect comp
Finance
Paper
Pharma
Real estate
Rubber
Semicond
Software
Tourism

Figure A2 – Estimated coefficients of other NC measures for different sectors, DEATH/POP







Source: authors' elaborations