Heterogeneity of technological structures between EU countries: an application of complex systems methods to Input-Output Tables

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Abstract

The identification of the channels through which a given shock spreads to the rest of the economy, determining its final impact, is essential to formulate effective policy interventions. Input-output tables (IOTs) are widely used to detect the network of intersectoral relations of a country - i.e., its sectoral technological structure or domestic supply chains - and the role of different sectors in the propagation of a shock. However, the heterogeneity that characterize the technological structures of different countries is inevitably a source of complexity for the development of supranational and timely coordinated policies because it requires to analyse and interpret a large amount of information. This paper proposes a unique problem setting that aims to deal with this complexity by facilitating the analysis and visualization of similarities and differences among the technological structures of countries, relying on the identification of a small number of archetypes and showing how their interpretation could be exploited to support the definition of coordinated policy interventions. Specifically, non-negative matrix factorization is used to extract the archetypal matrices of the technological structures of the 28 European countries from IOTs, revealing dense intersectoral relationships and a low degree of heterogeneity between them. Then, random walk indicators are applied to study shock propagation within these archetypes, uncovering sectoral centralities. Finally, COVID-19 lockdown restrictions are analysed to exemplify the use of the proposed approach for coordinated policy action.

1 Introduction

The onset of the COVID-19 pandemic has focused renewed attention on the relevance of developing tools and frameworks to inform coordinated policy making across different countries. For instance, at the European Union (EU) level, the pandemic has induced governments to design and implement massive economic interventions to limit the severity of the public health emergency for citizens, societies, and economies (European Commission, 2020) and stimulate recovery.[1] In issuing these measures, the European Commission (EC) stressed the relevance of

[1]In April 2020, the European Commission (EC) promoted two packages of interventions: the Coronavirus Response Investment Initiative (CRII) and the Coronavirus Response Investment Initiative Plus (CRII+). This action was supplemented on 27 May 2020 with the REACT-EU package. In addition, existing funds have been reoriented, and new funds have been made available in all EU Member States to tackle the COVID-19 crisis through the temporary recovery instrument called Next Generation EU and its centrepiece, the Recovery and

coordinating the interventions and obtaining an alignment of the EU members over the action plan, as the lack of coordination in the policy response may exacerbate negative externalities and accelerate the persistent reduction in economic openness, slowing down the recovery (European Commission, 2020). This point also appears particularly critical beyond the contingency of the pandemic. The EU is an economic and political union between sovereign countries that delegated some of their decision-making powers to EU institutions to set policy on specific matters of common interest. Therefore, the decision-making system calls for the identification of proposals and solutions that should be effective both at the supranational level (i.e., the EU), which aims to reach a "global" optimum, and at the local level (i.e., the national governments), which instead typically refers to a "local" optimum. All this requires a deep understanding of the channels through which a given policy impulse spreads to the rest of the economy, determining its final impact.

Among the different tools and frameworks that could be used to support coordinated policymaking, the input-output tables (IOTs) appear interesting for their informative potential. IOTs are a powerful instrument used to represent and analyze the production structure of an economy, perform impact analysis, or estimate the effects of various shocks affecting economic activity at different geographic levels (Miller and Blair, 2009, Oosterhaven and Polenske, 2009, Ten Raa, 2014, 2017). Specifically, IOTs describe the flows of intermediate and final goods and services within a country, considering several representative sectors, and provide a comprehensive picture of the interdependences among the different sectors, summarizing the flows across sectors in the matrix of technical coefficients (Leontief, 1936, 1951). In particular, this matrix offers a networked view of the production process describing how the output from one sector (origin) becomes an input to another (destination) sector, i.e. the domestic supply chains at sectoral level. For this reason, a broad stream of literature has employed instruments of network analysis to analyze economic systems using IOTs[2] and estimate how economic shocks propagate throughout them (Gabaix, 2011, Acemoglu et al., 2015), thus providing new insight to support policymaking.

Despite their popularity, the application of IOTs for supporting coordinated policy decisions at the European level is not immediate. The IOTs are available at the country level and represent the production structure and the related economic flows that characterize every country. Hence, the analysis of the different national IOTs for supporting coordinated supranational decision-making remains quite complex since it first requires analyzing and interpreting a large amount of information available for several countries and then needs to synthesize them into a single common proposal without losing contact with each national system.

The approaches proposed in the literature to "put together" the information of different IOTs do not balance the two aspirations – i.e., make a synthesis at a supranational level and remain in contact with the national level. On the one hand, most works that compare different countries rely on a set of indicators extracted from IOTs (see, e.g., Díaz et al. 2006). In this way, a small set of arbitrary covariates is extracted from complex data, and a relevant part of the information is lost, as similarities and differences among different countries are reduced in one or a few indicators. On the other hand, other works looking at one unique global network comprising many countries with the corresponding economic structures (see De Benedictis and Tajoli 2011, Cerina et al. 2015, Amador and Cabral 2017, among others), do not consider the specific domestic productive linkages that characterize every single country, resulting in a limited comprehension of the constraints to the whole system that derive from what occurs

Resilience Facility. See: `https://ec.europa.eu/regional_policy/en/newsroom/coronavirus-response/` and `https://ec.europa.eu/info/strategy/recovery-plan-europe_en#background`.

[2]See, e.g., Fagiolo et al. (2008), Reyes et al. (2008), Gai and Kapadia (2010), Schiavo et al. (2010), Wu and Jiang (2011), Acemoglu et al. (2012), Kagawa et al. (2013), Carvalho (2014), Elliott et al. (2014), Glasserman and Young (2015), Xing et al. (2016), Amador and Cabral (2017), Carvalho and Thabaz-Salehi (2019), among others.

within each national system. The COVID-19 health crisis has highlighted that the structure of domestic productive linkages can significantly contribute to the vulnerability of an economic system, both locally and globally. Lockdown measures, including the interruption of several productive activities, resulted in an immediate disruption of the domestic supply chains as well as the emergence of imbalances at the global level.[3] This motivates the current debate on the identification of those sectors that are more relevant for different national supply chains and across different countries and production systems (see, e.g., Guan et al. 2020, Guerrieri et al. 2020, Ivanov 2020b, Mandel and Veetil 2020, Pichler and Farmer 2021.

Based on these considerations, we borrow from the field of Complex Systems, and in particular from the approach developed by Marron and Alonso (2014)[4], to propose a statistical pipeline, i.e. a unique problem setting, that:

1. supports the analysis and visualization of similarities and differences among the technological structures of several countries, in terms of the sectoral composition of domestic intermediate inputs used in the production of a given sector (or domestic supply chains)[5] based on the identification of a small number of archetypes;

2. shows how the reference to the archetypes can be helpful for supporting the development of coordinated policies, e.g., to foster recovery after common shocks hitting several economies or sectors.

Our pipeline starts by extracting a small number of fundamental matrices of technical coefficients, labeled *archetypes*, using non-negative matrix factorization (NMF) (Paatero and Tapper, 1994, Lee and Seung, 1999, 2000) of the matrices of technical coefficients of selected countries. Each archetype captures a specific feature of the sectorial structure of intermediate inputs of countries in terms of backward linkages between each sector and its domestic supplier industries without altering the original data. Therefore, the domestic supply chains of each country can be described as a mix of such a small number of archetypes, with a relevant reduction in the data complexity. In our application, using national IOTs from the World Input-Output Database (WIOD; Timmer et al. 2015, 2016) [6], the structures of intermediate inputs of the 28 EU countries are a mix of only three archetypes. Then, the archetypes serve as a key to reading and analyzing the pre-shock equilibria of the interdependencies among domestic sectors to be used as a benchmark for developing policy measures at a system-wide level. In this work, we contextualize this analysis within the COVID-19 lockdown scenario but, more generally, it constitutes an exercise that can be performed constantly at the EU level to design and develop common coordinated policies at the sectoral level affecting multiple countries.

Specifically, we study the shock propagation dynamics within the domestic supply chains, e.g., as generated by the deployment - for a few months - of lockdown restrictions aimed to promptly address the spread of COVID-19 pandemic, using the archetypes for the computation of topological centralities related to the detection of the most central sectors in a production system. For this purpose, we apply the random walk model proposed by Blöchl et al. (2011) for IOTs. Their approach focuses on a small external shock, which does not change the current

[3]According to Elliott (2021), in 2020, 70% of firms reported COVID-19-related domestic supply chain temporary interruptions and 84% of businesses reported delay in their cross border activities. In particular, 40% of these cases have occurred in tier 2 suppliers and beyond, highlighting the importance of detecting the critical tier along the upstream supply chain.

[4]This work belongs to the so-called object-oriented data analysis, a branch of studies in rapid expansion within the complex system field, which aims to adapt statistical methodologies to complex data (*e.g.*, by extending them to data taking values in separable Hilbert space.)

[5]In this paper, we use "technological structure", "structure of intermediate inputs" and "domestic supply chains" as synonyms to refer to the inter-sectoral linkages synthesized by the matrix of technical coefficients.

[6]Data and documentation of the WIOD project are available at `https://www.rug.nl/ggdc/valuechain/wiod`.

structure of the underlying national economy and excludes potential structural changes. We believe that this framework is sufficiently coherent with the sectoral shutdowns adopted at the outbreak of the COVID-19 crisis. First, although the pandemic had a significant impact on the global economy, the activity of the so-called “nonessential” sectors - especially those related to commercial and personal services - has been locked or limited only for a few weeks or months. In contrast, only a few sectors addressed a relevant decrease in their activity level due to mobility restrictions. In both cases, rather than a permanent destruction of production capacity that would have induced forward sectors to look for substitutes, the lockdown measures have represented a sort of temporary stand-by situation. Second, any substitution effect would have been difficult at the national and international levels, due to the rapid global spread of the COVID-19 and the almost simultaneous adoption of lockdown measures that immediately affected international trade.

To show the use of archetypes for guiding coordinated policy action, starting from their identification, we detect the centrality of sectors by applying the original Blöchl et al. (2011) algorithm, which considers a supply shock that occurs with equal probability in any sector. This allows us to identify the most vulnerable sectors in the abstract. Then, we propose a weighted version of their algorithm on the archetypes to simulate the COVID-19 lockdown measures that shut down different sectors in multiple countries with different intensities. The point here is that, rather than using a hypothetical scenario, we refer to these contingent sectoral shutdowns as a real, interesting case of prompt measures adopted to address an asymmetric shock affecting all EU countries almost simultaneously and for a limited period not exceeding some weeks or months.

Such an application reveals how the analysis of a few archetypes, representing the “meta-economic” technological structure of EU countries, can provide useful signals for a timely understanding of the specific consequences arising from the diffusion of a system-wide shock impacting sectors with different intensities. In addition, we show how patterns of similarities synthesized by the archetypes can be used to evaluate the impact of policy measures widely adopted by EU countries, providing support to policymakers for the design and implementation of coordinated policies measures.

The rest of the paper is organized as follows. Section 2 briefly reviews the main works that have inspired our approach. Section 3 is devoted to the introduction of the basic concepts of IOTs and presents the WIOD dataset. Section 4 details the methodology. The experimental setup is reported and discussed in Section 5, while Section 6 presents and discusses the results. Section 7 offers some concluding remarks.

2 Related works

Originating from the classical political economy, the IOTs we know today are a tool introduced by Leontief (1936) that describes the economic structure of a country, provides comprehensive detail on sectoral interdependence, and shows how the different parts of the economy fit together, influencing one another. The analysis of the domestic intersectoral linkages is the main purpose of the input-output framework (Miller and Blair, 2009), and the so-called interindustry or intermediate input matrix (see Section 3) contains the basic information of the input-output analysis. Specifically, its columns allow us to define how inputs from different sectors combine in the production process of a specific industry. At the same time, its rows present how a sector’s output distributes along the user industries, offering a view of the production process as a complex network of transactions between suppliers and users.

The importance of these intersectoral relationships has led different scholars to study the structural properties of IOTs, developing different methods for the identification of key sectors, such as the use of backward and forward interindustry linkages as measures of structural interdependence (Chenery and Watanabe, 1958, Rasmussen, 1956, Hirschman, 1958), minimum flow analysis (Schnabl, 1995), fields of influence (Sonis and Hewings, 1991, 1992), and the fundamental economic structure (FES) approach (Simpson and Tsukui, 1965, Jensen et al., 1991, Thakur, 2008, 2011), among others.

In the last two decades, this research area has been flourishing thanks to both the impressive expansion of network analysis and visualization tools and the availability of large datasets, providing homogeneous IOTs for several countries and years and allowing for direct comparisons across countries, sectors, and periods [7]. All these advances have offered a fresh approach for the analysis of complex networks associated with intersectoral relationships derived from IOTs.

International trade benefits more from these advancements in investigating the structure and characteristics of international production networks, the position of different countries in global value chains, and their interdependences. A common approach starts with simple network metrics[8] - e.g., the average degree of the network, the node degree, and the average geodesic distance among nodes - and then adds centrality measures to detect the position of each country or sector and to assess its relevance within the network (see Fagiolo et al. 2008, Reyes et al. 2008, De Benedictis and Tajoli 2011 and De Benedictis et al. 2014, among others). A crucial step is the identification of supply chains at the national or global level. Here, the main issue is given by the complex nature of IOTs: since sectors are part of different value chains, it is difficult to separate them. Several studies attempt to overcome this issue by employing different techniques, but their solutions generally come at the cost of altering the original data. For instance, the fuzzy clustering algorithm employed by Díaz et al. (2006) allows sectors to belong to different value chains. However, to adopt this technique, authors first need to compare IOTs, derive a set of covariates from the IOTs, add other economic system characteristics from other data sources, and then perform a Principal Component Analysis to assess the relative importance of these features. Therefore, the results obtained using this technique do not directly take into account the original IOTs data. Additionally, Dietzenbacher and Romero (2007) studied the interdependencies between industries in different countries from a global value chain perspective, measuring the distance between two industries through the average propagation length and altering the original data compiling an intercountry IOT from the national IOTs of the analyzed countries and further aggregating the table to eight industries. Another approach to this data complexity problem is found in Argüelles et al. (2014), which excludes some sectors from the analysis according to the distribution of their output before applying hierarchical clustering on principal components. Again, although this technique might lead to a better cluster analysis, the results are potentially biased due to subjective judgments on which sectors to keep in the analysis.

More recently, to overcome these limits, some scholars have started to adopt network community partition algorithms based on NMF, a method for uncovering hidden features in complex networks (see Section 4.1 for details) that have already been applied to perform community detection (Wang and Huang, 2017, Li et al., 2018, Chen et al., 2020) or blind source separation in different fields, such as genomics (Frigyesi and Höglund, 2008), text mining (Ding et al., 2008) and sound and image recognition (Bisot et al., 2016). In economics, Kagawa et al. (2013) have utilized this technique to address the problems of data complexity when IOTs are considered. Based on environmental IOTs and focusing on the Japanese automobile supply chain, these authors applied NMF to detect polluting clusters, suggesting these sectors to cooperate to reduce their environmental impact. Then, Kanemoto et al. (2018) extended the analysis

[7]These datasets include e.g.: the OECD Input-Output database; the TiVA database by OECD; the World Input Output Database (WIOD); the Global Trade Analysis Project (GTAP); the Asian International Input Output (IDE-JETRO) and the MRIO-Eora dataset.

[8]A multitude of metrics describing the statistical properties of networks and capturing their peculiar characteristics has been developed by network theory and then applied and adapted to different domains (see Newman 2010 for a general overview and Jackson 2011 for a review on networks in economics).

considering all the supply chains in the Japanese economy and identified 58 carbon-intensive clusters of industries with higher carbon reduction potential.

In this regard, the NMF approach seems particularly well suited to identify a small number of features of the domestic supply chains that emerge from IOTs and are common to different countries. In this respect, NMF is a tool to reduce the complexity and multidimensionality of the problem while synthetizing into a parsimonious number of objects (archetypes) the networks represented by the domestic intersectoral linkages. Instead of extracting some indicators from the data, NMF results in a reduced matricial representation that can be rapidly analyzed without altering the original data. This paradigm is the main feature and advantage of NMF compared with other approaches originating from both network theory and other aforementioned fields of studies, such as those of Schnabl (1995) and Sonis and Hewings (1991). As an example, Schnabl (1995) argues that IOTs fail to capture the actual technological structures of countries, criticizing the use of the matrix of the technical coefficients as a tool to capture the technological interlinkages of an economic system and proposing an alternative matrix derived from it. However, even such alternative representation could be used as a starting point of the pipeline we propose, albeit at the cost of introducing an additional level of complexity, as it constitutes an elaboration of the data that, as such, introduces further modeling assumptions. Specifically, in our pipeline, dimensionality reduction and the interpretation of the tables are conducted according to a principle not present in the previous literature: minimizing the actual reconstruction error of the original matrices.

Our work also presents some connections with the wide variety of economic and financial studies that uses contagion algorithms to investigate how shock propagation contributes to the stability conditions of a system and of network techniques to analyse the relevance of participants in a system (see, e.g., Eisenberg and Noe 2001, Acemoglu et al. 2012, Bisias et al. 2012, Battiston et al. 2012 among others). Within the multitude of methods proposed to analyze similarities and differences between networks, centrality measures have taken a key role in these studies. Most of these measures of centrality define the structural relevance of a node through a random walk perspective (see Masuda et al. 2017 for a very comprehensive review of random walk applications to networks). However, as argued by Blöchl et al. (2011) such centrality measures are difficult to apply to IOTs since these tables are directed and almost completely connected graphs with self-loops. To overcome these issues, Blöchl et al. (2011) extended two vertex centrality measures to IOTs, represented as weighted and directed networks *de facto* either fully connected or very sparse and with self-loops, i.e., with intrasectoral linkages representing the output of a sector that is used as its own input. As a consequence, these measures are designed to quantify the propagation of an indivisible supply shock arising in a given sector and have a clear economic interpretation: random walk centrality identifies the sector most rapidly affected by the shock, while the counting betweenness allows to detect the sector where the shock lingers longest. In our analysis, we adopt the random walk measure proposed by Blöchl et al. (2011) to assess the sectoral vulnerability of domestic supply chains to any external shock in terms of rapidity. Moreover, in order to exemplify the use of our pipeline in a real-world case, we propose a weighted version of this measure that is capable of properly investigating the immediate changes in sector centrality due to a specific shock, such as the shutdown measures that in the first months of 2020 affected some sectors with different intensities.

This application has been inspired by the growing stream of research on the COVID-19 pandemic that use the sectoral interdependencies extracted from IOTs as a part of different IOTs-related frameworks to study the economic impacts in terms of GDP and/or employment (see, e.g., Bonet-Morón et al. 2020, Fadinger et al. 2020, Giammetti et al. 2020, Guan et al. 2020, Haddad et al. 2021, Pedauga et al. 2021, Pichler and Farmer 2021, Villani and Fana 2021). Beside strictly economic assessment, some scholars used input-output analysis to detect the effects of COVID-19 pandemic from an environmental perspective. Focusing on Italy, Bazzana et al. (2022) estimate the final effects of the pandemic in terms of energy consumption and CO2 emissions. Other strands of literature used IOTs to capture the domestic intersectoral linkages to assess the impacts of lockdown measures. It is not surprising that Italy, the first Western country to confront with the spread of COVID-19 and to adopt lockdowns, is used as a case study by different scholars. For instance, Bonfiglio et al. (2022) estimate the cross-region and cross-sector economic impacts, in terms of GDP and employment, of the different mobility restrictions imposed by the Italian governments along the successive waves of the pandemic, proposing a non-linear programming model based on a multiregional IOT. They emphasize that the first emergency measures on the sectors to be closed did not consider their role within the overall structure of the economy but observe that the analysis of these intersectoral linkages was increasingly included in the design of successive interventions, leading to more flexible and tailored policy measures. Focusing on the lockdown measures adopted between March and June 2020, Cottafava et al. (2022) use the Italian IOT sourced by Eurostat and the input–output inoperability model to predict the economic and environmental effects of the 2020 restrictions, identifying the most interconnected and, thus, crucial sectors for the propagation of current external shocks and testing different future scenarios. Also, these authors stress the need to take into consideration the degree of productive linkages existing among sectors in the design of effective industrial policies and recovery measures.

Finally, IOTs are used with an impact analysis framework to assess the economic effects of the financial packages and reconstruction plans to revive the economy after COVID-19. Using a static multi-regional input-output model and the WIOD Database, Picek (2020) calculates a preliminary impact of the Next Generation EU - which includes the new European Recovery and Resilience Facility - and presents the cumulative increase in national real GDP over the period 2021-2027 and its yearly averages for all EU countries. For Italy, the Italian National Institute of Statistics (Istat, 2022) provides an impact assessment of the investments set out in the Italian Recovery and Resilience Plan related to transport infrastructures and sustainable mobility, estimating through the national IOT their economic impact in terms of value-added and employment by sector. Then, by applying the tools of network analysis to the matrix of technical coefficients, Istat (2022) investigates the mechanisms and channels of transmission of the shock within the domestic production system, highlighting the structural characteristics of the network of intersectoral relations and the role of different sectors in the propagation of the stimulus from different investment sectors to the rest of the system. In particular, the results in terms of sector centrality show that three sectors (*Construction, Other manufacturing, and Manufacture of fabricated metal products*) absorb about 65% of the investments but have a peripheral position within the national economy and therefore have a limited transmission capacity of the impulse.

Among the different techniques adopted to estimate the negative economic consequences occurring when one or more industries cease to operate, the IOTs framework has been widely used thanks to its detailed sector-level information and ability to provide information on interlinkages between sectors of the economy. Therefore, since the pandemic led to production slowdown in the affected economies and relevant supply chain interruptions, at first sight, our application also presents some connections with the strand of impact analysis related to the supply chain effects of unexpected events, such as catastrophic disasters due to a natural or man-made hazard or infrastructure failure, called disaster analysis (Okuyama, 2007, Steenge and Bočkarjova, 2007, Okuyama and Santos, 2014, Koks et al., 2016, Koks and Thissen, 2016, Xia et al., 2019). Indeed, within the literature on the consequences of COVID-19, some scholars adopted disaster analysis and different input-output models to estimate the effects of the pandemic on environmental and economic indicators distinguishing amongst sectors thanks to the ability of this approach to capture the supply chain effects of mobility restrictions (e.g., Lenzen et al. 2020, Pomponi et al. 2021, Cottafava et al. 2022). More in general, disaster analysis has developed several variations of the standard input-output model. For instance, one of the most commonly used models is the inoperability input-output model (IIM) (Okuyama, 2014, Okuyama and Yu, 2019) and its dynamic extensions (DIIM), which introduce industry resilience coefficients (see Dietzenbacher and Miller 2015 for a review of this model). The need to analyze changes in intersectoral interdependencies, i.e., in the technical coefficient matrix, is at the ground level of the generalized hypothetical extraction method (Dietzenbacher and Lahr, 2013, Dietzenbacher et al., 2019), which can also be implemented to identify key sectors in input-output production networks (Giammetti et al., 2020). However, our statistical pipeline differs from this method for different reasons.

First, our focus is not that of assessing the relevance of a sector given its hypothetical extraction centrality but rather on assessing its stochastic centrality. Indeed, the main purpose of this work is to investigate the heterogeneity of the technological structures of EU countries, not manipulating original data but by extracting a parsimonious list of latent matrices of the technical coefficients that can be effectively used to support coordinated and timely policy decision-making processes. The archetypes that we detect maintain as much information as possible and provide a data object through a procedure in line with the particular data structures of IOTs. Then, the random walk measure mimics the spread of instability through the supply chain due to a shock occurring in a specific sector. This allows the identification of the most vulnerable (central) sectors, taking into account several different scenarios, i.e. in the abstract, offering a view of the sectors that are in general crucial for the domestic supply chains, without requiring to simulate for each sector the extraction from IOTs of the corresponding row and column and compare with the pre-extraction production structure. We believe that this aspect is relevant when timely policy actions are needed, particularly when addressing shocks affecting multiple sectors and countries. Hence, the archetypes identify a few key technological structures composing each national IOT, thus avoiding computing the hypothetical extraction for many different IOTs. At the same time, the approach we employ to compute the centrality of the n sectors for each of the k archetypes allows for greater computational parsimony, in line with our idea of reducing to the bare minimum the complexity of the problem. Assuming that the number of archetypes is small, we have that to compute the centrality of each node we are required to invert a matrix for each one of them, entailing a number $kO\left(n^3\right) = O\left(n^3\right)$ of computations. On the other hand, hypothetical extraction works by censoring each sector of the table and then performing an inversion for each one of them, taking into account the final demand vector as well. From a computational point of view, this requires $knO\left(n^3\right) = O\left(n^4\right)$ operations. Although the computational benefit might seem small when n is of the dimension of the problem under scrutiny, it is certainly true that the difference would become more evident as n grows. This issue has led us to prefer a network approach, conceptually more in line with the Complex System framework to which our work refers.

Second, hypothetical extraction is used in the input-output literature to deal with shocks that affect both the supply and demand sides. However, our focus is on the structure of intermediate inputs to support coordinated policies in a specific area, e.g., to address the vulnerability of specific sectors within domestic supply chains. Indeed, it is noteworthy that most of the network literature on value chains and shock propagation focuses on one unique international network, where nodes are the countries and bilateral flows of trade, investment, etc. stand for the edges. However, Cerina et al. (2015), in a study of cross-countries sectoral relationships in global value chains observe that although supply chains are becoming more international, the vast majority of transactions is still occurring within countries. When all countries collapse in a single global network, as in Cerina et al. (2015), the distinction between the countries of the network is somewhat lost. Therefore, our paper differs from the large majority of the literature and deals simultaneously with several networks since we aim to deduce some common fundamental technological structures underlying the IOTs of multiple different countries.

Finally, the hypothetical extraction method is strictly associated with disaster analysis. Our statistical pipeline, specifically developed to support a coordinated and timely policymaking process, can even be applied to evaluate the effects of positive shocks, despite, in this paper, the application we propose to introduce our approach is focused to a negative shock.

More in general, it is worth mentioning that our work does not aim to investigate long-term macroeconomic trajectories after the COVID-19 pandemic with IOTs data, but it simply exploits the lockdown phase to illustrate the application of our proposed approach when a temporarily significant shock imposes the design of common and timely interventions. Moreover, our focus on the spatial relations between economies felt more important, especially in light of the effort the EU has to develop coordinated policy actions.

Concerning the temporal dimension, it should be specified that input-output analysis is a static model, although there have been attempts to analyze and model the dynamics of IOTs, as in Sonis et al. (1996). As the main objective of temporal analysis is to understand, in retrospect, the impact of a certain policy or shock on an economic system, this aspect of the problem might not be of great significance for the implementation of measures as those undertaken to confront an exceptional and unprecedented event as the COVID-19 pandemic. Lockdown measures are a unique example of significant temporary supply-side restrictions that, on the one hand, allow them to reduce contagion and, on the other hand, impact the potential output of an economy. Lockdown measures prevent the full utilization of production factors, possibly impacting sectoral interdependencies and altering the contributions of production factors to potential output. As observed by Bodnár et al. (2020), the level of potential output in the lockdown phase depends on the full capacity of the economy: for instance, if we assume that available factors of production do not vary with lockdown (unchanged degree of full capacity), when restrictions are gradually lifted then production factors will be fully utilized again; if instead, we assume that during the lockdown none of the resources are available for production (hence a drop in the full capacity due to a remarkable temporary decline of supply), the lifting of mobility restrictions will progressively allow the degree of full capacity to recover its pre-crisis level.

3 Input-Output Tables: basic concepts and data

A national IOT is a schematic representation of all monetary flows of final and intermediate goods and services between producers and users/consumers within a country in a given year. The economy is divided into several sectors, and the IOT shows how the output from one sector becomes an input to another.

In particular, let $I = \{1, 2, \dots, n\}$ be the set of indices associated with each sector. We define z_{ij} as the monetary value of the transactions that occurred between sector i and sector j, that is, the flow of intermediate goods or services. If we let f_i be the final (domestic and foreign) demand for sector i, and x_i the total quantity of goods i produced in the country, we obtain that for every $i \in I$,

$$x_i = \sum_{j=1}^{n} z_{ij} + f_i. \tag{1}$$

Considering all the sectors, if we set $x = (x_1, \dots, x_n)$, $f = (f_1, \dots, f_n)$, $\mathbf{Z} = (z_{ij})_{i,j \in I}$ and we indicate by $\mathbf{1}$ the vector of length n composed of 1s, we can rewrite in a more compact form the previous equation as:

$$x = \mathbf{Z}\mathbf{1} + f. \tag{2}$$

In our study, we focus on the network of interindustrial relationships that emerge from $\mathbf{Z}$, the so-called inter-industry or intermediate input matrix, where row entries represent outputs from a given sector, and column entries represent inputs to a sector. In particular, these inter-sector relationships are summarized by technical coefficients, that is, the input requirements per unit of output obtained as follows:

$$a_{ij} = \frac{z_{ij}}{x_j},\ i, j \in I, \tag{3}$$

with $a_{ij} \in [0, 1]$, for $i, j \in I$. Let $\mathbf{A} = (a_{ij})_{i,j \in I}$; we call $\mathbf{A}$ the $(n \times n)$ matrix of technical coefficients of a country, which stays at the ground level of our methodology.

To obtain IOTs, we rely on the WIOD dataset - release 2016 [9] (Timmer et al., 2015, 2016), which offers a higher level of harmonization of statistical data across countries and time. It covers 43 countries (and a model for the rest of the world) and 56 sectors of activity (according to the ISIC nomenclature Rev.4; see Table 1 for the full list of sectors and the abbreviations used in this paper) for the period 2000-2014. We focus on the most recent available year, 2014, and all 28 EU countries at that date, namely, Austria, Belgium, Bulgaria, Croatia, Cyprus, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Netherlands, Poland, Portugal, Romania, Slovakia, Slovenia, Spain, Sweden, United Kingdom. We retain 54 of the 56 sectors, as in many countries two sectors - namely *Activities of households as employers; undifferentiated goods and services-producing activities of households for own use* and *Activities of extra-territorial organisations and bodies* - have zero final output and, therefore, are removed from the study.

4 Methodology

We propose a two-steps methodology to perform a cross-country analysis of the structure of domestic productive linkages emerging from national IOTs:

1. we perform NMF on the 28 vectorized matrices of technical coefficients of EU countries to extract fundamental technological structures from IOTs (archetypes) and express the domestic supply chains of each country as a mix of these archetypes, focusing on intermediates and the sectoral backward linkages;

2. we exemplify the use of these archetypes employing the centrality measure proposed by Blöchl et al. (2011) to examine forward linkages through their vulnerability to external supply-side shock, also using lockdown measures generally enacted by countries during the COVID-19 pandemic to identify an example of some specific sectoral shutdowns.

This Section details this two methodological steps. We however remark that, although outside of the scope of this work, at step 2. of the methodology different centrality measures could be used in place of that of Blöchl et al. (2011). In particular, the centrality measures being used should be chosen according to the specific aim of the analysis. In particular, note that the methods reviewed in Section 2 to interpret IOTs, can also be used to provide an interpretation to the archetypes resulting from step 1.

4.1 Nonnegative Matrix Factorization

The necessity of approximating a matrix using another one of lower rank naturally arises in many problems of statistics and machine learning. In the usual context, a matrix $\mathbf{X} \in \mathbb{R}^{m \times n}$ is

[9]This release of the WIOD dataset is publicly available for free at `https://www.rug.nl/ggdc/valuechain/wiod/wiod-2016-release`.

Table 1: WIOD sectoral coverage

ISIC Code	Sector
A01	Crop and animal production, hunting and related service activities
A02	Forestry and logging
A03	Fishing and aquaculture
B	Mining and quarrying
C10-C12	Manufacture of food products, beverages and tobacco products
C13-C15	Manufacture of textiles, wearing apparel and leather products
C16	Manufacture of wood and of products of wood and cork, except furniture; manufacture of articles of straw and plaiting materials
C17	Manufacture of paper and paper products
C18	Printing and reproduction of recorded media
C19	Manufacture of coke and refined petroleum products
C20	Manufacture of chemicals and chemical products
C21	Manufacture of basic pharmaceutical products and pharmaceutical preparations
C22	Manufacture of rubber and plastic products
C23	Manufacture of other non-metallic mineral products
C24	Manufacture of basic metals
C25	Manufacture of fabricated metal products, except machinery and equipment
C26	Manufacture of computer, electronic and optical products
C27	Manufacture of electrical equipment
C28	Manufacture of machinery and equipment n.e.c.
C29	Manufacture of motor vehicles, trailers and semi-trailers
C30	Manufacture of other transport equipment
C31-C32	Manufacture of furniture; other manufacturing
C33	Repair and installation of machinery and equipment
D	Electricity, gas, steam and air conditioning supply
E36	Water collection, treatment and supply
E37-E39	Sewerage; waste collection, treatment and disposal activities; materials recovery; remediation activities and other waste management services
F	Construction
G45	Wholesale and retail trade and repair of motor vehicles and motorcycles
G46	Wholesale trade, except of motor vehicles and motorcycles
G47	Retail trade, except of motor vehicles and motorcycles
H49	Land transport and transport via pipelines
H50	Water transport
H51	Air transport
H52	Warehousing and support activities for transportation
H53	Postal and courier activities
I	Accommodation and food service activities
J58	Publishing activities
J59-J60	Motion picture, video and television programme production, sound recording and music publishing activities; programming and broadcasting activities
J61	Telecommunications
J62-J63	Computer programming, consultancy and related activities; information service activities
K64	Financial service activities, except insurance and pension funding
K65	Insurance, reinsurance and pension funding, except compulsory social security
K66	Activities auxiliary to financial services and insurance activities
L	Real estate activities
M69-M70	Legal and accounting activities; activities of head offices; management consultancy activities
M71	Architectural and engineering activities; technical testing and analysis
M72	Scientific research and development
M73	Advertising and market research
M74-M75	Other professional, scientific and technical activities; veterinary activities
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
P	Education
Q	Human health and social work activities
R-S	Other service activities
T	Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use
U	Activities of extraterritorial organizations and bodies

given. Each column of $\mathbf{X}$ represents a data point in a m-dimensional space. We are interested in approximating $\mathbf{X}$ through the product of two matrices, $\mathbf{W} \in \mathbb{R}^{m \times k}$ and $\mathbf{H} \in \mathbb{R}^{k \times n}$, so that

$$\mathbf{X} \approx \mathbf{WH}. \tag{4}$$

In other words, we are willing to find a k-dimensional representation for the data points of $\mathbf{X}$. The columns of $\mathbf{W}$ constitute the basis, whereas those of $\mathbf{H}$ the coordinates of each point. Depending on the problem, it is possible to use several well-known techniques (Gillis, 2011), such as Principal Component Analysis (PCA) where we impose orthogonality on the columns of $\mathbf{W}$ and to the rows of $\mathbf{H}$, considering the Frobenius norm to estimate the error (Johnson and Wichern, 2014), or k-medoids, a vector quantization technique (Hastie et al., 2009). In the present study, if we set $\mathcal{N} = \{1, \ldots, n\}$ and $\mathcal{M} = \{1, \ldots, m\}$, we can write $\mathbf{X} = \{x_{ij}\}_{i \in \mathcal{M}, j \in \mathcal{N}}$, the data points in $\mathbf{X}$ lying in a space whose components are non-negative, namely $x_{ij} \geq 0$, $\forall i \in \mathcal{M}, j \in \mathcal{N}$. It is thus of interest to impose the same constraint on $\mathbf{W}$ and $\mathbf{H}$. This particular specification of a low-rank matrix approximation is known as *non-negative matrix factorization* (Paatero and Tapper, 1994, Lee and Seung, 1999, 2000). The non-negativity constraint on $\mathbf{W}$ allows us to interpret its columns as archetypes (or meta-genes). Analogously, the columns of $\mathbf{H}$ can be interpreted as coefficients (weights) signaling the importance of an archetype to that particular point.

In this work, $\mathbf{X}$ will be composed of the juxtaposition of vectorized matrices of technical coefficients (with $a_{ij} \geq 0$, $\forall i, j \in I$). Here NMF allows us to extract a small number of archetypes and related non-negative reconstruction coefficients: by rewriting the domestic productive linkages of each country as a non-negative mix of archetypal technical coefficient matrices, we can assess their level of adherence to the former[10].

To perform the NMF, we need to specify the loss function that measures the distance between the original matrix $\mathbf{X}$ and the product of $\mathbf{W}$ and $\mathbf{H}$ and addresses the most complex aspect of NMF, that is, the selection of the rank (k), which controls the dimensionality reduction (a smaller rank leads to a more parsimonious representation but may lead to an excessive reconstruction error).

We adopt the loss function implemented in `Scikit-Learn` (Pedregosa et al., 2011), a Python library employed throughout a vast number of machine learning applications that is therefore well tested and subject to the scrutiny of many developers. The loss function adopts a state of the art elastic-net penalisation scheme:

$$d_{\text{Fro}}(X, WH) + \alpha\rho||W||_1 + \alpha\rho||H||_1 + \frac{\alpha(1-\rho)}{2}||W||^2_{\text{Fro}} + \frac{\alpha(1-\rho)}{2}||H||^2_{\text{Fro}}, \tag{5}$$

where the first term serves to compute the reconstruction error, whereas the other terms are used to set how parsimonious the low-dimensional representation should be: the L1 penalisation induces sparsity and the L2 penalisation regularises the coefficients[11]. As is common to the vast majority of methods of dimensionality reduction, the most controversial implementation aspect of the loss function is the choice of the parameters, *i.e.*, α and ρ. To address this issue, we

[10]In contrast, PCA is not well suited for our application since it performs dimensionality reduction using a projection on spaces spanned by eigenvectors. While this is useful in many cases, it provides no constraints on the positivity of the data, which is a fundamental characteristic of the technical coefficient matrices. Moreover, PCA rewrites the data according to the direction of maximum variance, and we could obtain tables capturing only those sectors that vary the most amongst countries.

[11]Different formulations of NMF can be found in Lee and Seung (1999, 2000), Cichocki et al. (2008), Tan and Fevotte (2013). Loss functions are also explored in Berry et al. (2007), Chu et al. (2004), Smaragdis et al. (2014), Zhang et al. (2008). Computational methods applied to NMF are instead studied in Lee and Seung (2000), Cichocki et al. (2009), Berry et al. (2007), Kim et al. (2007), Lin (2007). A review is found in Gillis (2011).

follow a widely adopted technique performing a *grid search* to explore different combinations of parameters and find the best combination.

For the rank selection, in line with the standard workflow of machine learning studies, we implement the Bi-Cross-Validation technique for NMF exposed in Owen and Perry (2009). The main idea is that to censor a random $(k \times k)$ matrix and then reconstruct the censored matrix, thus assessing the error. We show the algorithm in Algorithm 4.1.[12]

[1] Let $\mathbf{X}$ be an entry-wise non-negative matrix of dimensions $(m \times n)$, let $\mathcal{I}_l \subset \{1, \ldots, m\}$ and $\mathcal{J}_l \subset \{1, \ldots, n\}$ be, respectively, a row and column holdout subsets for $l \in \{1, \ldots, L\}$, where L is a positive integer. Let $\mathcal{K} \subseteq \{1, \ldots, \min\{m, n\}\}$ be a set of ranks. Let $\mathbf{A}^+$ denote the Moore-Penrose inverse of $\mathbf{A}$.

$k \in \mathcal{K}$ $\mathrm{BCV}(k) = 0$

$l \in \{1, \ldots, L\}$ and $k \in \mathcal{K}$ $\mathcal{I} = \mathcal{I}_l$ and $\mathcal{J} = \mathcal{J}_l$ $\mathbf{H}^{(k)}_{-\mathcal{I},-\mathcal{J}}, \mathbf{W}^{(k)}_{-\mathcal{I},-\mathcal{J}} = \mathrm{NMF}(\mathbf{X}_{-\mathcal{I},-\mathcal{J}}, k)$ $\hat{\mathbf{X}}^{(k)}_{\mathcal{I},\mathcal{J}} = \mathbf{X}_{\mathcal{I},-\mathcal{J}} \left(\mathbf{H}^{(k)}_{-\mathcal{I},-\mathcal{J}}\right)^+ \left(\mathbf{W}^{(k)}_{-\mathcal{I},-\mathcal{J}}\right)^+ \mathbf{X}_{-\mathcal{I},\mathcal{J}}$ $\mathrm{BCV}(k) = \mathrm{BCV}(k) + \left|\left|\mathbf{X}_{\mathcal{I},\mathcal{J}} - \hat{\mathbf{X}}^{(k)}_{\mathcal{I},\mathcal{J}}\right|\right|^2_F$

4.2 Network Analysis

Traditional centrality measures used in social network analysis (i.e., Freeman's closeness centrality) ignore self-loops. We compute the vulnerability of the archetypal productive linkages following Blöchl et al. (2011), which have been the first to propose a random walk measure for input-outupt networks that incorporate self-loops.[13] Finally, we use the lockdown measures as a suggestive real-world case to identify the sectors affected by shocks with different magnitudes.

The economic intuition beyond the measure by Blöchl et al. (2011) is simple. Within a network of transactions among the sectors of an economy, a sector plays a key role if it is very close to all other sectors and, as a consequence, an external supply-side shock quickly reaches this key sector, regardless of where it has been generated. Then, they propose to measure the distance between nodes using the mean first-passage time (MFPT) (Bollobás, 2001) of a shock randomly propagating through the network and assuming that the most central sectors are those where shocks arrive faster, i.e., in a few steps. In particular, in their model shocks are traced from the sector where they have origin until the end of their random journey, after which they are assimilated by final demand.

Formally, we define a graph $G = (V, E)$, where $V = \{1, \ldots, n\}$ is the set of n nodes, each one corresponding to a sector of the economy, and $E \subset (V \times V)$ refers to the linkage between sectors. To each $(i, j) \in E$, a weight a_{ij}, corresponding torespective entry of the matrix $\mathbf{A}$ of the technical coefficients, is assigned. Let $i \in V$ be a node, its *strength* can thus be written as follow:

$$k_i = \sum_{j=1}^{n} a_{ij},$$

and its *neighborhood* as

$$N(i) = \{j \mid (i, j) \in E\}.$$

Note that to express missing edges, Blöchl et al. (2011) is set whenever necessary a_{ij} to zero. In our application, to guarantee the convergence of their indicator, we have to add a very small

[12]Different solutions are found in Brunet et al. (2004), Frigyesi and Höglund (2008) Hutchins et al. (2008), Bioucas-Dias and Nascimento (2005), Tan and Fevotte (2013), Gillis (2014), Squires et al. (2017) based on different model-assessment methods (such as the decrease of the reconstruction error, Bayesian method and criterion based on information theory).

[13]We also perform a standard PageRank algorithm (Page, 2001), first developed by Lawrence Page and widely employed during the first years of Google™. The algorithm counts the number and the quality of links to a node, assuming that the most important nodes are the ones that are most often linked to and are linked to by important nodes. Results are available on request.

noise to the zero edges randomly sampled from a uniform distribution taking values between in $[10^{-8}, 10^{-4}]$. We set the number to be this small to avoid an excessive perturbation of the matrices of technical coefficients, whose values range between 0 and 1.

To model the flows of goods between sectors of an economy, Blöchl et al. (2011) consider a *random walk* (Borgatti, 2005) to investigate the transition probabilities modeling how one unit of output produced by one sector might be bought from another, were it to be sold without being split. Thus, they normalize according to the rows of the matrix. To this aim, it is necessary to create a matrix $\mathbf{K}$ that is equal to the various k_is on the diagonal and zero otherwise and use this matrix to compute the transition matrix:

$$\mathbf{M} = \mathbf{K}^{-1}\mathbf{A}.$$

If we let $s \in V$ and $t \in V$, it is possible to define the probability that a random walker going from s to t employs exactly r steps to move from the source to the destination node as:

$$\mathbb{P}\left(s \xrightarrow{r} t\right)$$

Therefore, the MFPT from node s to node t is defined as:

$$H(s,t) = \sum_{r=1}^{+\infty} r\,\mathbb{P}\left(s \xrightarrow{r} t\right). \tag{6}$$

Notice that for all t, $H(t,t) = 0$ as $\mathbb{P}\left(t \xrightarrow{r} t\right) = 0$ for all $r \geq 1$. Thus, Blöchl et al. (2011) can define the *random walk centrality* of the nodes in an input-output graph as:

$$C_{rw}(i) = \frac{n}{\sum_{j \in V} H(j,i)}. \tag{7}$$

According to Blöchl et al. (2011), the indicator of Eq. (7) has a straightforward economic interpretation: if a supply shock is about to hit a node with uniform probability, a high random walk centrality of a sector implies that it will most likely be affected in a short time.

The partial or complete closure of all nonessential productive and commercial activities and services due to the spread of COVID-19 is the most direct supply-side effect of nonpharmaceutical interventions implemented to contain the health crisis during the lockdown phase. Hence, it is well comparable to the external supply-side shock modeled by Blöchl et al. (2011).[14] However, actual emergency measures implemented during lockdown did not affect sectors with uniform probability. To apply Eq. (7) for the COVID-19-like scenario, we thus slightly modify the original indicator, adjusting the centrality of nodes according to the shutdown level referred to the various economic sectors. To this aim, we assign to each sector i a non-negative weight p_i, obtaining the following indicator:

$$C_{wrw}(i) = \frac{\sum_j p_j}{\sum_{j \in V} p_j H(j,\, i)}. \tag{8}$$

Moving from the unweighted case to a scenario in which some nonessential sectors have rather high weights, and all the others have weights tending to zero means increasing the original distances between sectors without changing the network's structure. Consequently, the centrality of sectors will be influenced more by sectors that weigh more, and in particular, the centrality of the essential sectors from the nonessential ones will decrease. Note that (7) is a particular case of (8), as we obtain the former whenever all weights are equal.

[14] Please note that with this approach we observe only a partial impact of the COVID-19 pandemic, i.e., the supply-side shock that is strictly and immediately related to the shutdowns measures, thus mapping the shock propagation model of Blöchl et al. (2011). Nevertheless, it is worth noting that lockdown measures also impacted the demand side, whose shocks are not included in our approach.

5 Experimental setup

In this section, we present some specific implementation details of our statistical pipeline. Subsection 5.1 describes the NMF setup, focusing on the parameter setting and rank selection. Subsection 5.2 presents the implementation details to adapt the random walk indicator proposed by Blöchl et al. (2011) to the example of application related to the COVID-19 lockdown scenario.[15]

5.1 NMF: Parameters and Rank Selection

After extracting IOTs from the WIOD database, computing the **A** matrix of technical coefficients for each country, vectorizing all the **A** matrices and juxtaposing them to obtain **X**, a vector of 54^2 rows, the crucial aspect of NMF implementation is the *grid search* to obtain the parameters α and ρ of the loss function (5).

For each number of ranks, we compute the reconstruction error for 5000 random submatrices. We also consider the case in which the rank is null, and in this case, we do not approximate the censored matrix but we only compute its Frobenius norm. Figure 1 shows the results for increasing ranks. By observing the silhouettes, a sensible pair of values appears to be $\alpha = 0.20$ and $\rho = 0.05$. We use these parameters to perform NMF.

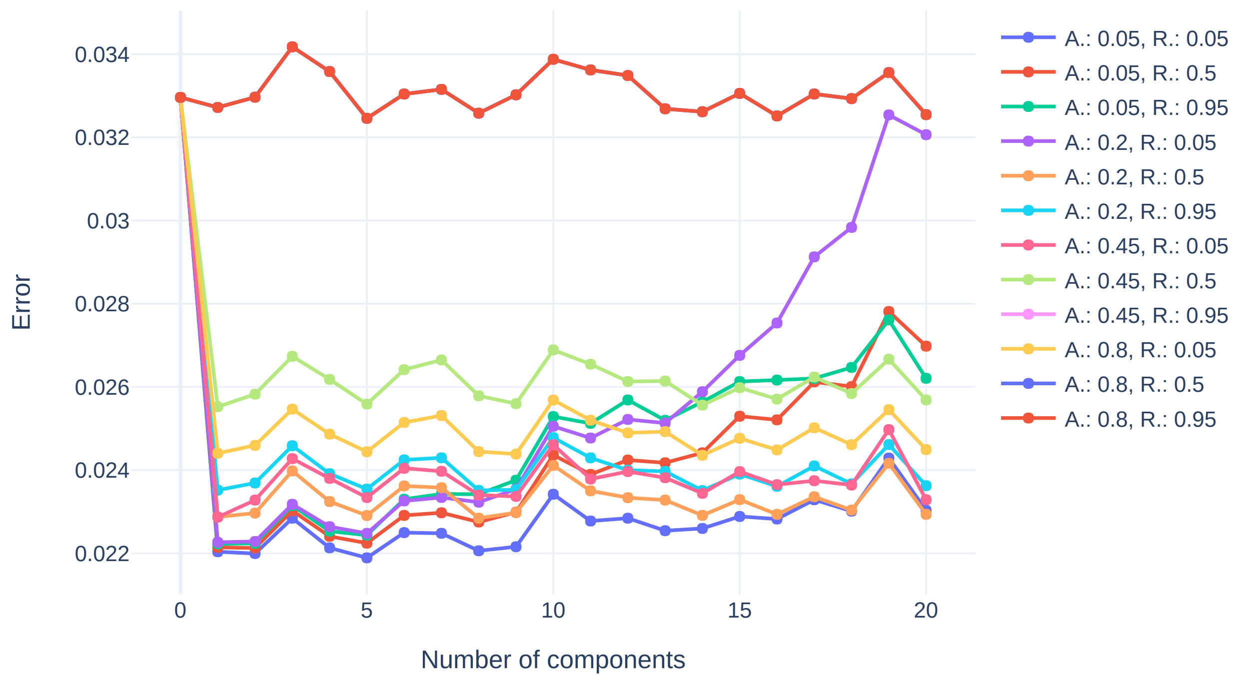


Figure 1: NMF Bi-Cross Validation reconstruction error applied to the 2014 WIOD Dataset, obtained by iteratively censoring (3×3) random submatrices. We considered 5000 iterations. The zero component model is obtained by averaging the norms of the censored data. Different penalties are reported.

[15] For reproducibility purposes, the code is available on GitHub at `https://github.com/mascaretti/input-output-paper/`.

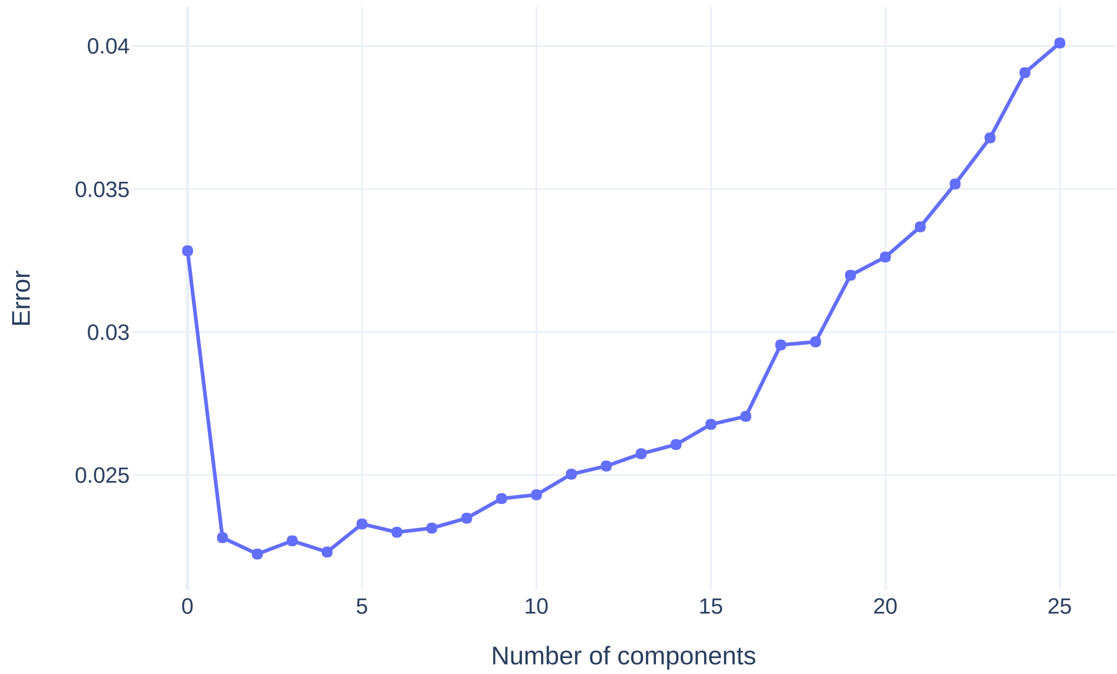


Figure 2: NMF Bi-Cross Validation reconstruction error applied to the 2014 WIOD Dataset, obtained by iteratively censoring (3×3) random submatrices. We considered 10000 iterations. The zero component model is obtained by averaging the norms of the censored data.

In the last step, after selecting α and ρ, we combine the NMF with the bi-cross-validation method to find the best rank. Despite being a solution that requires a substantial amount of computational time, this approach guarantees at least a uniform exploration of the set of the different tuning possibilities, thus making the choice of parameters more robust. More specifically, we run this bi-cross-validation doubling the number of iterations per rank to 10000 to obtain a very reliable estimate for the number of archetypes. Results shown in Figure 2 suggest us to select $k = 3$.

Therefore, our matrix $\mathbf{W}$ will consist of a number $k = 3$ columns and 54^2 rows, representing the archetypal matrices of technical coefficients extracted from the original data. On the other hand, $\mathbf{H}$ will contain the coefficients used for reconstructing the EU national IOTs and consists of $k = 3$ rows and 28 columns. If $k = 3$ and a country has coefficients say $(0.43; 0.02; 0.08)$, then to reconstruct its original matrix of technical coefficients, we will do $0.43A_I + 0.02A_{II} + 0.08A_{III}$, with $A_{\{\}}$ being the matrix of archetype I, II, III.

5.2 Random Walk Centrality setting: an example of application to the COVID-19 lockdown scenario

In addition to the application of the original random walk indicator proposed by Blöchl et al. (2011), to exemplify different levels of sectoral shutdown that can characterize the policy actions, we test a weighted version using as reference the lockdown measures implemented to tackle the emergence of the COVID-19 pandemic.

COVID-19 pandemic evolution induced governments to introduce mobility restrictions, which generated a change in consumption habits and heavily affected the supply side by limiting the activities of nonessential sectors and impacting the labor supply of people not allowed to reach workplaces. To present a practical approach to evaluate policy responses to the COVID-19 shock, we analyze the lockdown phase to show how restrictions affecting economic sectors with different intensities generate a propagation of shocks with competing trajectories depending on the selected archetype.

Following a growing body of literature investigating the socio-economic effects of the COVID-19 pandemic (see, e.g., Baqaee and Farhi 2020, Bonadio et al. 2020, Çakmaklı et al. 2020, del Rio-Chanona et al. 2020, Guerrieri et al. 2020, Inoue and Todo 2020, McKibbin and Fernando 2021, Papanikolaou and Schmidt 2020, Spelta et al. 2020, Bonaccorsi et al. 2021, Smolyak et al. 2021, among others), we propose to apply the shock propagation here described to study the supply side effects of policy interventions. Shocks in one sector might be amplified by a reduction in the demand for intermediate goods from other sectors, with decreased output impacting wages, income and demand, thereby leading to an overall impact with higher imbalances (Guerrieri et al., 2020). A drop in the workforce or a shift in the preference between savings and consumption may generate additional negative effects that may propagate in the supply chain and cause second-order negative impacts generating a self-reinforcing downward spiral in economic output. As argued by del Rio-Chanona et al. (2020), large negative shocks from the supply side can be mitigated by quick aggressive fiscal and monetary policies that minimize cascade effects on labor supply and income inequality. In particular, del Rio-Chanona et al. (2020) find that the negative effects of the COVID-19 pandemic evolution on supply and demand may have different levels of persistence depending on the sector, with aggregate effects that are likely to be dominated by supply shocks due to the importance of many manufacturing and services sectors that are not considered essential and for which their workforce is unable to perform the same activities from home. Hence, the presence of constraints on labor force supply is assumed to be a key channel for the extensive losses from the supply side (see, e.g, Dingel and Neiman 2020, Koren and Pető 2020, McKibbin and Fernando 2021, Papanikolaou and Schmidt 2020). From a similar perspective, several studies also investigate the relevance of supply interlinkages at the global scale (see, e.g., Golan et al. 2020, Haren and Simchi-Levi 2020, Ivanov 2020a, Lenzen et al. 2020, Verschuur et al. 2021). For instance, Guan et al. (2020) show how substantial and heterogeneous effects propagate through global supply chains, with global coordination greatly reducing economic losses. With this regard, our proposed approach relates to the literature proposing mathematical tools for efficient solutions for tackling supply chain impacts due to COVID-19 uncertainty. For instance, Paul et al. (2022) propose a stochastic mathematical model to optimise supply chain recovery under multi-dimensional uncertainty related to singular and correlated disruptions in demand, supply, and production capacities, while sector specific scenarios have been discussed in a number of works (see, e.g., Belhadi et al. 2021, Burgos and Ivanov 2021, Govindan et al. 2020, Jha et al. 2021, Kenan and Diabat 2022). Our analysis relates to this literature proposing a statistical pipeline to evaluate sectoral impacts and guide coordinated policy interventions relying on a parsimonious representation of real-world economic interlinkages.

In line with preliminary studies that identify the sectors affected by partial or complete shutdowns in different countries (see, e.g., OECD 2020), we propose an illustrative application, and we assume a full shutdown in the manufacturing of transport equipment (*Manufacture of motor vehicles, trailers and semi-trailers* (C29); *Manufacture of other transport equipment* (C30)) and in the activities related to arts, sports, recreation and entertainment (*Other service activities* (R-S)); a shutdown of one-half in *Construction* (F) and professional service activities (*Real estate activities* (L); *Legal and accounting activities; activities of head offices; management consultancy activities* (M69-M70); *Architectural and engineering activities; technical testing and analysis* (M71); *Scientific research and development* (M72); *Advertising and market research*

(M73); *Other professional, scientific and technical activities; veterinary activities* (M74-M75)), and shutdowns of three-quarters are assumed in a few other sectors (*Wholesale and retail trade and repair of motor vehicles and motorcycles* (G45); *Wholesale trade, except of motor vehicles and motorcycles* (G46); *Retail trade, except of motor vehicles and motorcycles* (G47); *Air Transport* (H51) and *Accommodation and food service activities* (I)).

Finally, we assign to those sectors that remained open a weight of 1, a partial lockdown that stopped a sector for one half is given a weight equal to 10, a shutdown of three quarters is associated with a weight of 100, while full lockdown entailed a weight of 1000.

6 Results and discussion

In this section, we present the archetypes obtained from NMF (Section 6.1), also offering a visualization of these large and complex objects through heatmaps. Then, we analyze the vulnerability of these 'meta-economic' technological structures of the EU, following the random walk model proposed by Blöchl et al. (2011) to simulate the diffusion of a supply-side shock and our proposed weighted version to adapt it to the COVID-19 lockdown scenario (Section 6.2).

6.1 The archetypes

Applying the NMF to the 28 matrices of technical coefficients of EU countries, three different archetypal technological structures emerge, representing different paradigms of domestic value chains in terms of domestic supplier sectors of a given industry. Figure 3 reports the heatmaps of the archetypal technical coefficients matrices. Specifically, the column-to-rows intersections represent the exchanges of the user industry corresponding to the column from the different supplier sectors corresponding to the rows and vice-versa. The diagonal captures the intersectoral linkages. The colour scale shows the intensity of the linkages between two sectors: the darker the colour, the higher the exchange between sectors.

More specifically, Archetype I shows a pronounced activation on the diagonal, together with a diffused activation on several different sectors. It stands for an integrated economic system in which off-diagonal values show the relevance of intrasectoral linkages. In addition to the diagonal, we see the activation of *Electricity, gas, steam and air conditioning supply* (D), *Wholesale trade, except of motor vehicles and motorcycles* (G46), *Land Transport and transport via pipelines* (H49), *Warehousing and support activities for transportation* (H52), *Financial service activities, except insurance and pension funding* (K64), *Real estate activities* (L), *Legal and accounting activities; activities of head offices; management consultancy activities* (M69-M70) and *Administrative and support service activities* (N). Archetype II captures the importance of the *Wholesale trade, except of motor vehicles and motorcycles* (G46) and *Real Estate activities* (L) sectors, while the remaining sectors are poorly integrated with the rest of the system. Finally, Archetype III exhibits smaller activation in general, mainly distributed on the diagonal, and it seems to represent an economic system that is slightly more polarized towards a less interconnected domestic structure.

Then, we show how a single technological structure of countries can be expressed as a combination of the emerging archetypes. In Table 2 we report the weights of each archetype in composing each original national matrix of technical coefficients. The goal is twofold: on the one hand, we verify the effectiveness of our approach, showing how the archetypal matrices are consistent with those of the underlying countries; on the other hand, we assess the heterogeneity of the technological structures among EU countries.

First, using the heatmaps as a visualization tool, we compare each archetype with some of the original matrices of technical coefficients of countries. We select the countries with a high weight of that archetype within the mix. Figure 4 reports the corresponding heatmaps of

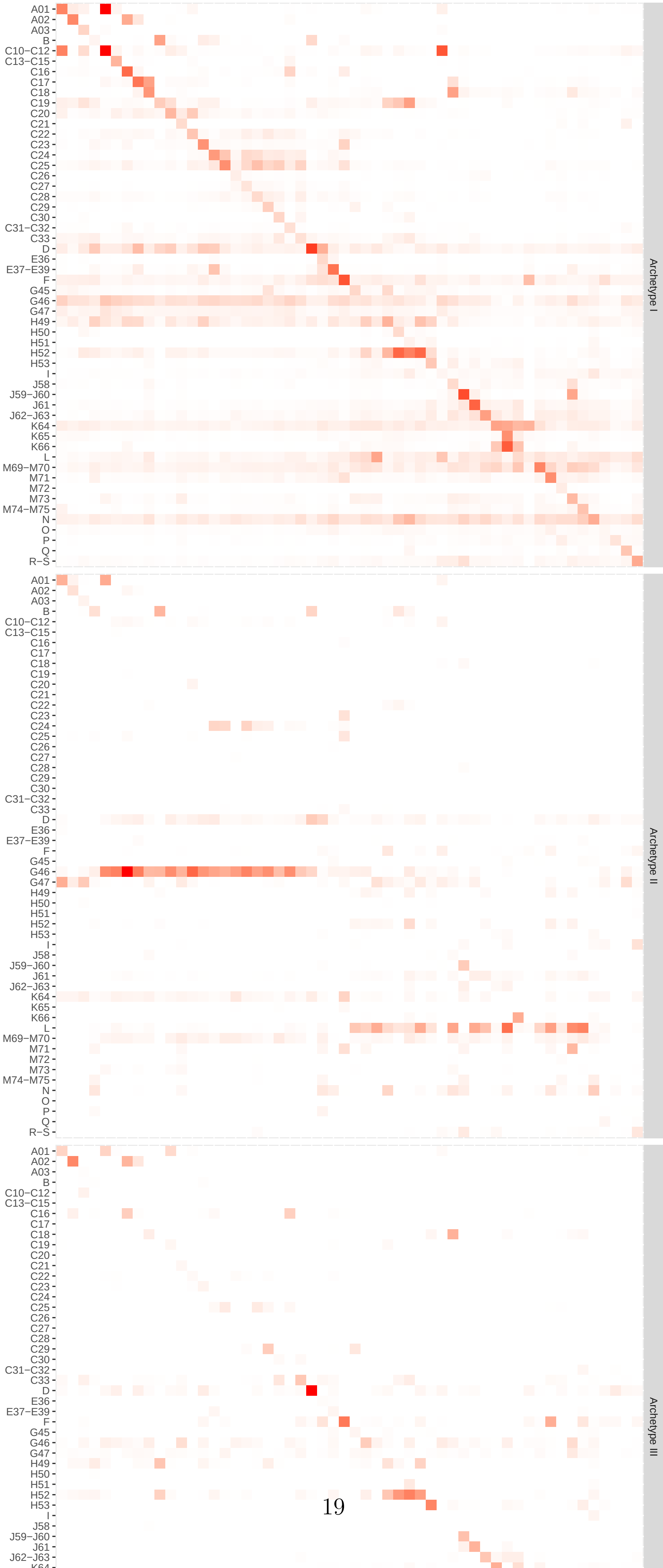

Archetype I
Archetype II
Archetype III
A01
A02
A03
B
C10−C12
C13−C15
C16
C17
C18
C19
C20
C21
C22
C23
C24
C25
C26
C27
C28
C29
C30
C31−C32
C33
D
E36
E37−E39
F
G45
G46
G47
H49
H50
H51
H52
H53
I
J58
J59−J60
J61
J62−J63
K64
K65
K66
L
M69−M70
M71
M72
M73
M74−M75
N
O
P
Q
R−S

Table 2: Matrix H: weights of each archetype in the country matrix of technical coefficients

Country	Archetype 1	Archetype 2	Archetype 3
Austria	0.913	0.087	0.000
Belgium	0.846	0.018	0.136
Bulgaria	0.577	0.293	0.130
Croatia	0.233	0.767	0.000
Cyprus	0.127	0.011	0.862
Czech Republic	0.846	0.053	0.101
Denmark	0.544	0.449	0.007
Estonia	0.766	0.171	0.063
Finland	0.842	0.158	0.000
France	0.843	0.147	0.010
Germany	0.875	0.081	0.044
Greece	0.094	0.890	0.016
Hungary	0.833	0.167	0.000
Ireland	0.875	0.062	0.063
Italy	0.900	0.088	0.012
Latvia	0.904	0.096	0.000
Lithuania	0.817	0.052	0.131
Luxembourg	0.727	0.273	0.000
Malta	0.899	0.000	0.101
Netherlands	0.875	0.125	0.000
Poland	0.832	0.116	0.053
Portugal	0.901	0.076	0.022
Romania	0.485	0.376	0.139
Slovakia	0.939	0.000	0.061
Slovenia	0.851	0.132	0.017
Spain	0.904	0.096	0.000
Sweden	0.834	0.166	0.000
UK	0.894	0.106	0.000

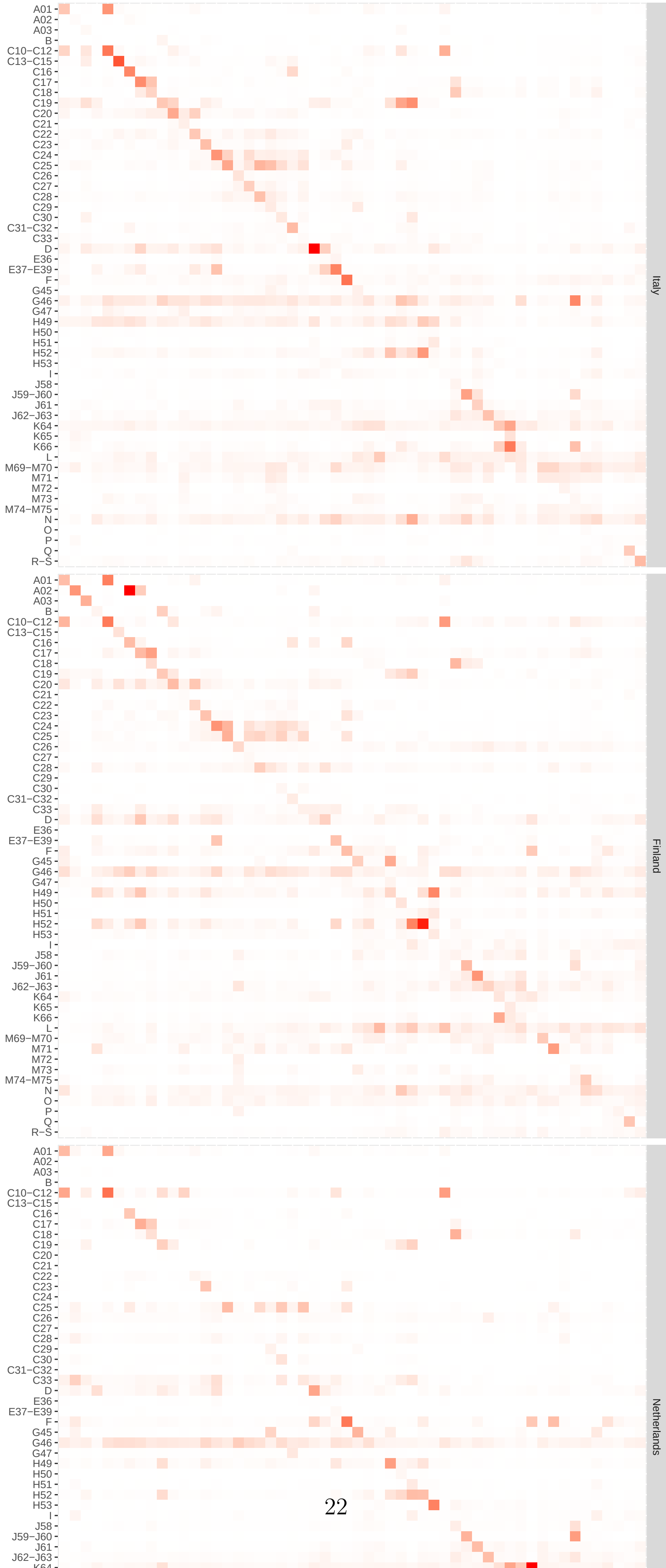
the matrices of technical coefficients of Italy, Finland and the Netherlands. These heatmaps appear closer to that of Archetype I in Figure 3, showing diffuse activation, especially on the diagonal. In fact, coefficients for Italy are $(0.900, 0.088, 0.012)$ and those for Finland are $(0.842, 0.158, 0.000)$. Moving to the Netherlands, we obtain a somewhat similar picture and a similar mix of archetypes: $(0.875, 0.125, 0.000)$.

We now focus on cases that show more dissimilarity. In Figure 5, we report heatmaps of the matrices of technical coefficients for Cyprus, Greece, and France. The first thing we expect is some similarity between France and Italy, at least if compared with Cyprus or Greece (see Table 2). We see that this holds, with coefficients of France $(0.843, 0.147, 0.010)$ close to the Italian ones. From Figure 5, we also notice that the technological structure of Cyprus is peculiar. We do not see a diffuse activation of sectors. Rather, the coefficients appear to be on average smaller, except for the diagonal. This resembles very much the Archetype III and such affinity is captured by the coefficients in Table 2: $(0.127, 0.011, 0.862)$. Finally, focusing on the Greece case, the visual impression reflects coefficients that are very much skewed onto the Archetype II. Indeed, the coefficients for Greece are $(0.094, 0.890, 0.016)$, and thus, the most central sectors are *Wholesale trade, except of motor vehicles and motorcycles* (G46) and *Real Estate* (L).

From this illustrative analysis, we, therefore, notice how two of the three archetypes specialize in describing two countries (namely, Greece and Cyprus), suggesting that their domestic supply chains are both different from each other and from those of countries such as France or Italy.

More generally, weights reported in Table 2 show that the Archetype I prevails in the majority of EU national technological structures, suggesting low heterogeneity among them. In Figure 6, we display the relative composition of the countries under scrutiny. Through this visualization, we see with more immediacy that the vast majority of the countries align towards Archetype I, suggesting that a supranational policy which affect the same sectors within the different countries would work similarly fashion across most of them, with the notable exception of Cyprus, Greece, and Croatia.

To summarize, using NMF, we address the multidimensionality issue related to the analysis of several national IOTs simultaneously, detecting three emerging archetypes and obtaining a relevant reduction in the objects to handle (i.e., from 28 to 3). It is a first advantage of our pipeline, which results particularly useful for supporting policy design since it reduces the computational effort (e.g. in terms of ex-ante impact analysis of different sectoral policies). Moreover, comparing the mix of archetypes underlying each country, we can assess the heterogeneity of the technological structures among countries.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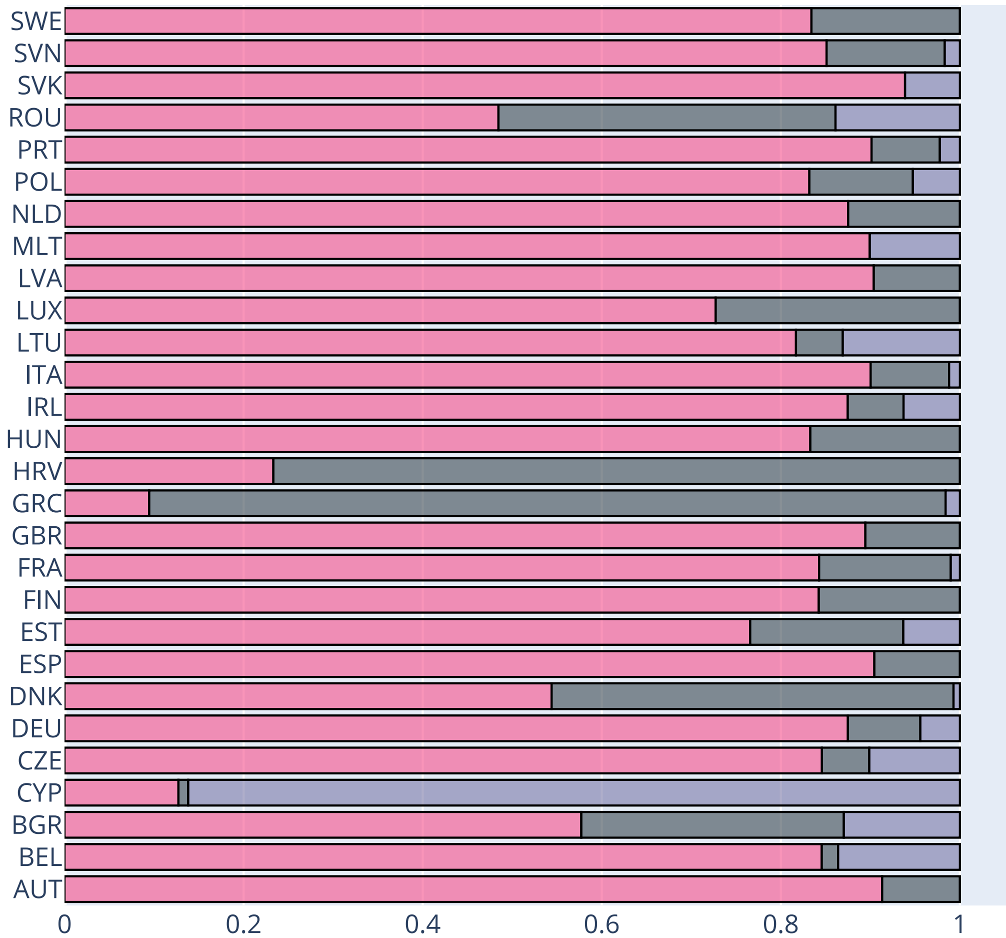

Figure 6: Relative Composition of EU Countries with respect to the Archetypes. Coefficients are normalized to sum to 1 to show the relative importance of the weights. The colour scheme is the following: the first archetype is pink, the second one is dark grey and the third one is violet.

6.2 Application to the COVID-19 lockdown policies in Europe

In this section, we exploit the three identified archetypes to exemplify the use of our proposed approach to design supranational and coordinated policy actions. To this aim, we use our weighted version of the random walk algorithm proposed by Blöchl et al. (2011) to observe the propagation of a specific supply shock, like the one related to lockdown restrictions promptly adopted by different countries at the outbreak of the COVID-19 crisis to impose the shutdown of non-essential sectors.

We first consider the synthetic representation of archetypes. Then, for each archetype, we compare the centrality of sectors in two different phases: before the COVID-19 outbreak, as a benchmark for the pre-shock economy, and during the lockdown, when sectors were impacted by policy restrictions with heterogeneous intensity. Specifically, for both phases, we report in Figures 7, 8 and 9 the coefficients of the sector centrality of the first, second and third archetypes, respectively. In particular, the figures displays in blue the unweighted centralities obtained from Eq. (7) by applying the Blöchl et al. (2011) algorithm, and in red, the weighted centralities obtained from Eq. (8) and related to the COVID-19 lockdown scenario. We recall that a high centrality means that the sector will most likely be affected in a short time by a given shock.

First, we can observe the sectoral centrality profile of each archetype and identify the most vulnerable sectors, focusing on the unweighted case. The most central sectors for Archetype I (Figure 7) are: i) *Advertising and market research* (M73), ii) *Air Transport* (H51) and iii) *Publishing activities* (J58). Regarding Archetype II, Figure 8 exhibits the emergence of three very central sectors: i) *Motion picture, video and television programme production, sound recording and music publishing activities* (J59-J60), ii) *Construction* (F) and iii) *Other service activities* (R-S). Shocks occurring in the economy are thus likely to generate high impact to these sectors. Finally, for Archetype III (Figure 9) we notice that the most central, and thus vulnerable, sectors are: i) *Insurance, reinsurance and pension funding, except compulsory social security* (K65), ii) *Air Transport* (H51), iii) *Construction* (F) and iv) *Accommodation and food service activities* (I).

Second, the unweighted centralities for the three archetypes indicate that values tend to be lower for Archetype I and, at the same time, are less skewed. Indeed, we observe that the sectoral centrality values of the Archetype I are more uniform among the different sectors compared to Archetype II and Archetype III, where some more marked sectoral peaks appear. It means that in Archetype I sectors will be hit by the shock almost simultaneously, i.e., its propagation is quite homogeneous along the different sectors. On the contrary, in Archetypes II and III the identified central sectors will be affected in a shorter time compared with the other sectors. Moreover, this result is in line with the archetypal economic structures emerging from Figure 3 and confirms that the domestic supply chains described by Archetype I are, on average, more interconnected. For this Archetype, we thus expect a rapid propagation of a supply-side shock to the whole economy.

Moving from the blue to the red points in Figures 7, 8 and 9, it is worth noting that the centrality profile in the COVID-19 lockdown scenario is not too different from the unweighted case. This first general result thus suggests that the propagation of shocks follows some rather homogeneous patterns, notwithstanding the differences in their origin. This stability also means that the unweighted average case can be used as a benchmark for a general shock.

More generally, as expected, in all archetypes, those sectors directly affected by shutdowns increase their centrality in terms of vulnerability to supply-side shocks. This is particularly visible for Archetype I (Figure 7), where most of the shutdowns sectors increase their centrality, with the only exception of *Accommodation and food service activities* (I) that record the same level of the previous application. In contrast, the other sectors have their centrality decreased, with the exception represented by *Repair and installation of machinery and equipment* (C33). Given the interconnected structures described by this archetype, this result seems to suggest that partial or complete shutdowns of the 15 considered sectors and the subsequent reduction in the supply of their goods and services do not immediately affect the supply from other sectors. That is because the shutdown sectors produce mainly final goods and services rather than provide intermediate inputs to other sectors.

For Archetype II (Figure 8), most of the shutdown sectors increase their centrality, with the only exception of *Air Transport* (H51), which does not change its level of vulnerability to supply-side shocks. All the other sectors show reduced centrality values, with the exceptions represented by *Publishing activities* (J58), *Manufacture of basic pharmaceutical products and pharmaceutical preparations* (C21) and, to a greater extent, *Motion picture, video and television programme production, sound recording and music publishing activities* (J59-J60). This suggests that these sectors have a direct impact from shutdown policy measures.

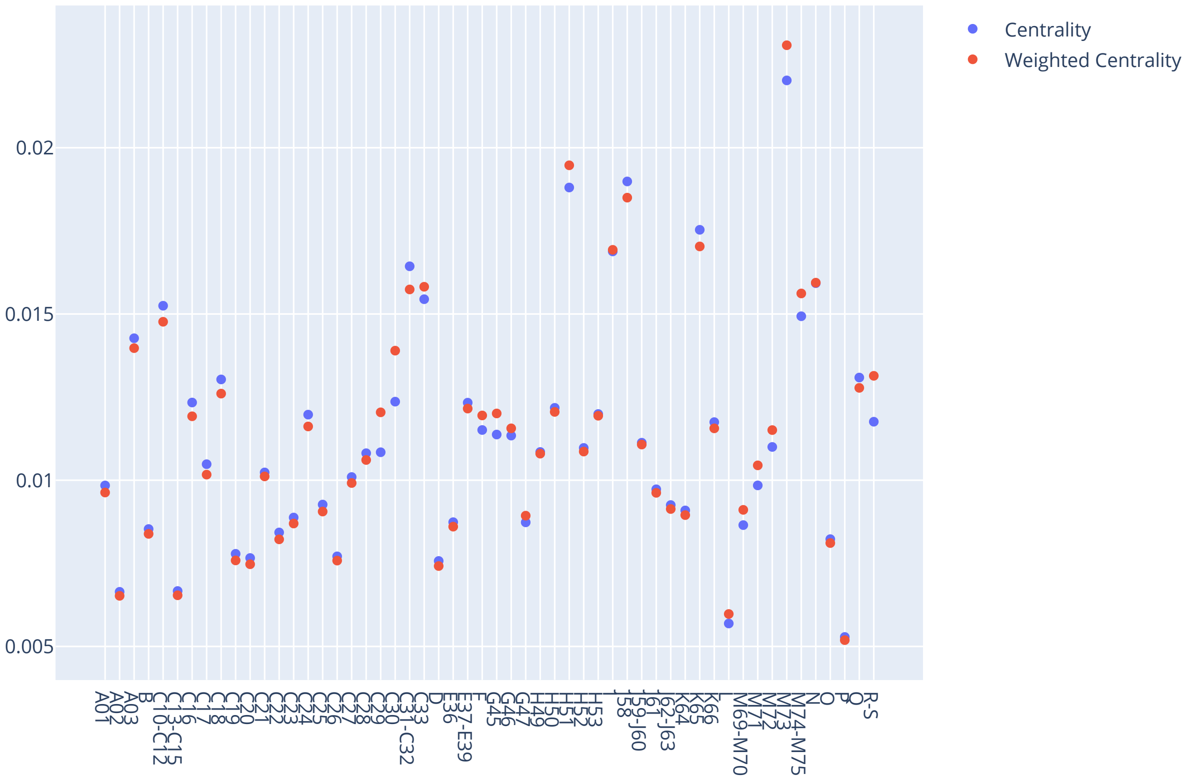

Figure 7: Sector Centrality for Archetype I.

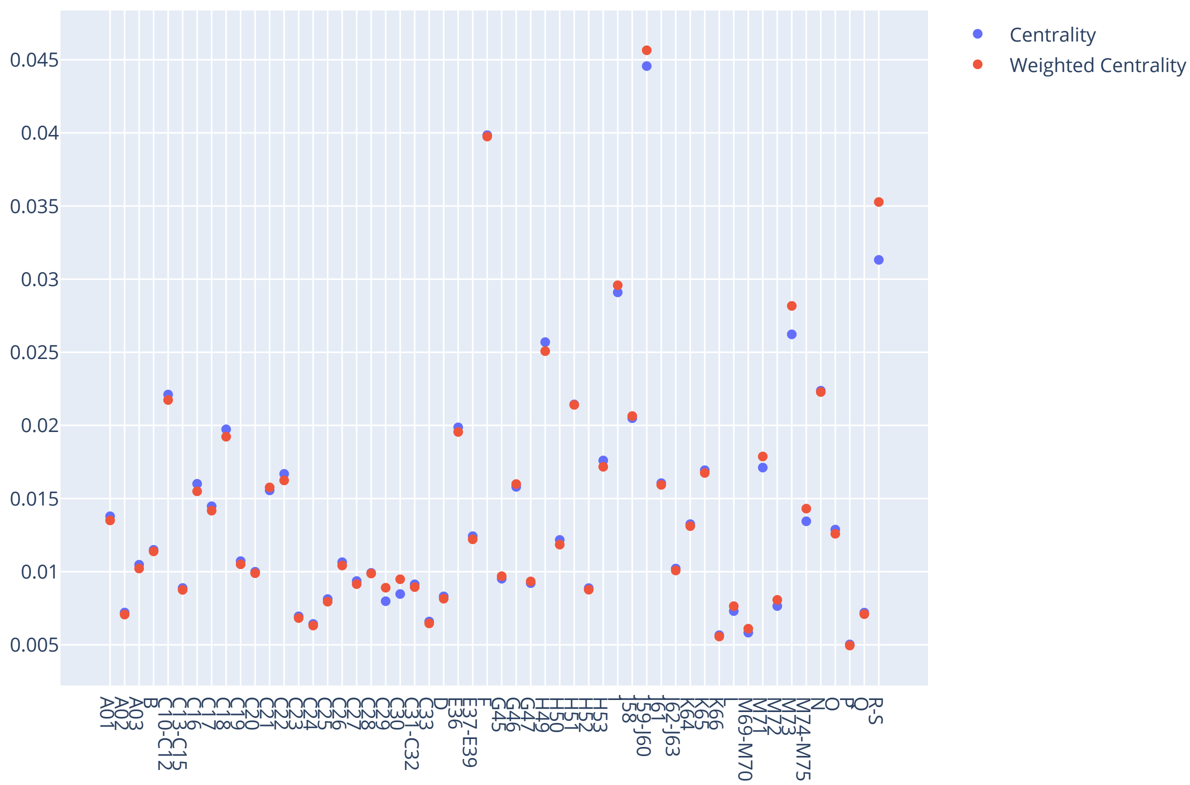

Figure 8: Sector Centrality of Archetype II.

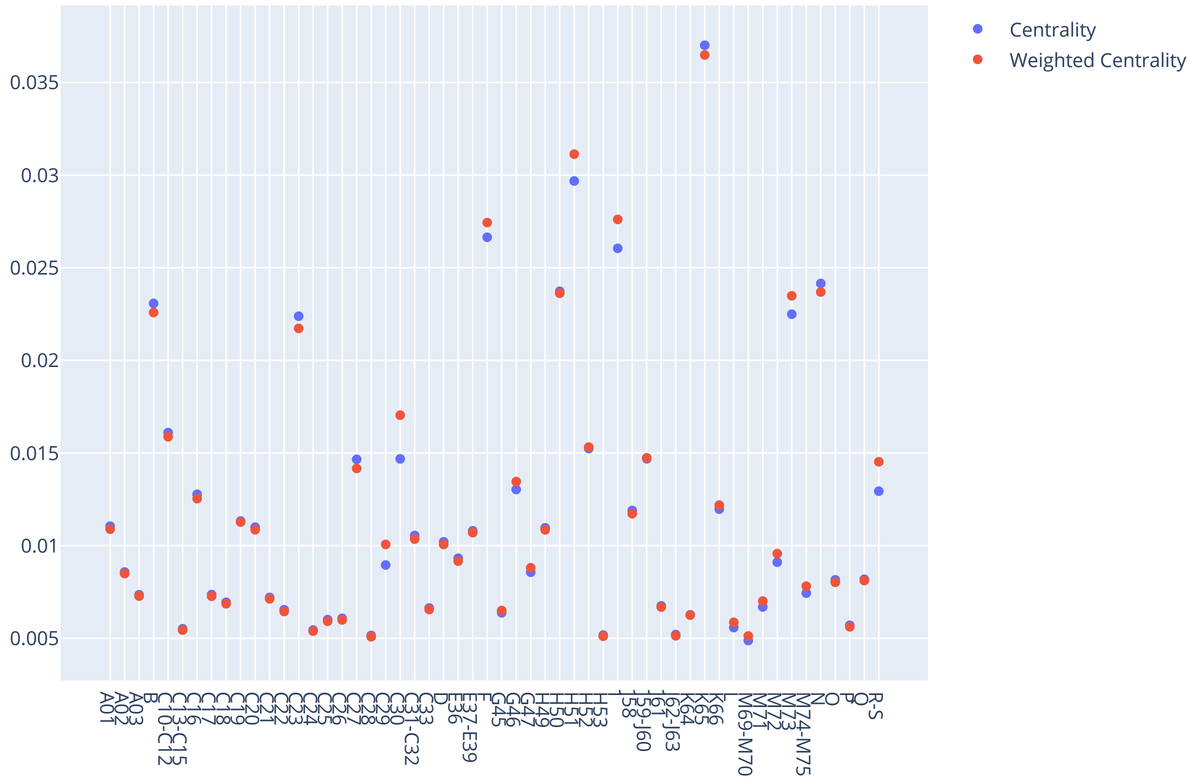

Figure 9: Sector Centrality of Archetype III.

Finally, analyzing Archetype III (Figure 9), the 15 sectors affected by partial or complete shutdowns increase their centrality together with the *Activities auxiliary to financial services and insurance activities* (K66) sector.

To conclude, Figure 10 shows the relative importance of each sector. This is done by showing the centrality scores computed across the archetypes. In this way, it is possible to concretely assess the importance of a sector by noting that its relative centrality is subject or not to changes depending on the archetype it refers to. For instance, we observe that four sectors, namely *Wholesale trade, except of motor vehicles and motorcycles* (G46), *Activities auxiliary to financial services and insurance activities* (K66), *Electricity, gas, steam and air conditioning supply* (D) and *Real estate activities* (L), reach very high values of centrality in some archetypes (mostly in the Archetypes II and III) but not in others. Given this high heterogeneity for these sectors, a precision policy should be envisaged in these cases. By contrast, the majority of the other sectors show a narrower range of dispersion of the maximum and minimum, indicating similar shock propagation across archetypes. Nevertheless, we can distinguish between those having an homogeneous centrality across archetypes and reaching also relatively high levels of it, like e.g. *Financial service activities, except insurance and pension funding* (K64) or *Telecommunications* (J61), and those instead in the lower tail of the centrality distribution, like e.g. *Human health and social work activities* (Q) or *Manufacture of textiles, wearing apparel and leather products* (C13-C16). Such sectors are likely to be vulnerable from shock propagation in a similar way across archetypes (maximum and minimum values are almost overlapped), with the former being in general more central given its higher level of centrality while the latter more marginal in the economic system. From a practical point of view, this synthesized visualisation can help policymakers identify those sectors for which a shock hitting the system has a greater likelihood of being imported (possibly in a similar fashion across archetypes), thus representing a tool to inform the policy decision-making process. In addition, although the application presented in this section refers to a negative shock, which causes business disruption and negative higher-order effects, the same framework can still be applied to design a positive impulse to the economy. In this regard, Figure 10 can be interpreted as a synthetic way to select production activities that are more likely to be influenced by shock propagation, which, for instance, can be of interest for policymakers interested in promoting recovery plans after the COVID-19 crisis.

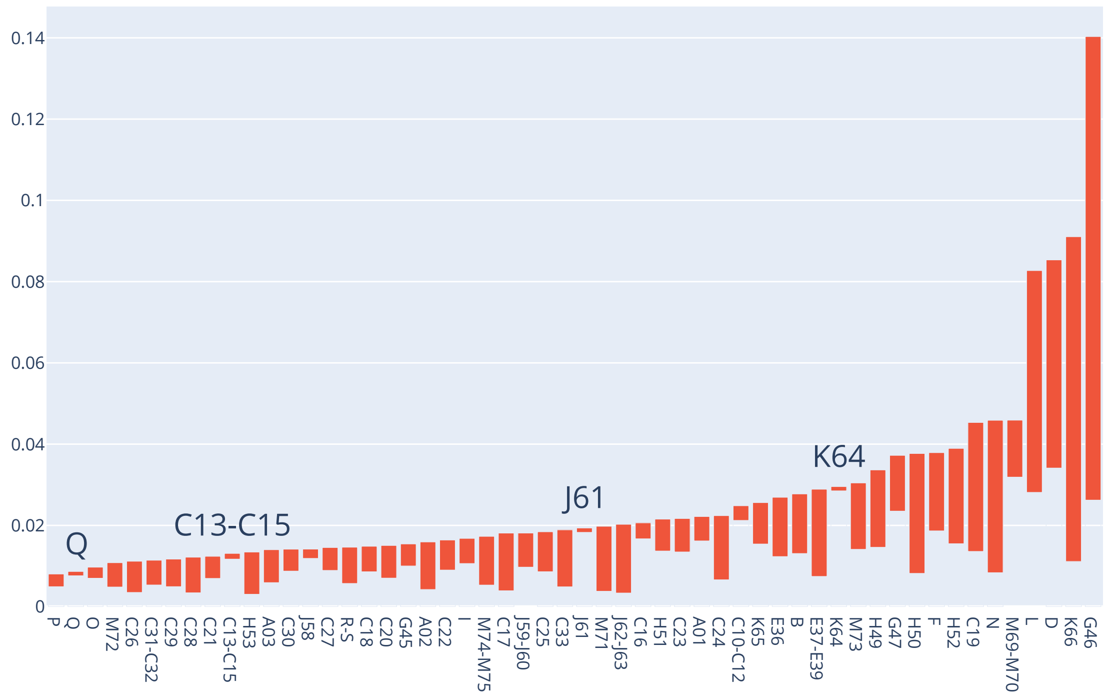

Figure 10: Minimum and Maximum Centrality of sectors. Red bars indicate the range, across archetypes, of the centrality values obtained for each sector. The four sectors with minimal range (Q, C13-C15, J61, K64) are highlighted.

7 Conclusions

Supranational policies define a general framework on a specific issue, which has to be declined into national implementation programs. If well-designed these policies could play a coordination role towards common goals. The design of effective supranational and coordinated policies across different countries requires to assess the impacts that the same policy measure has on different economies. It is a complex task that requires to analyse and compare a large amount of data and information about different countries.

To address this issue, we propose a statistical pipeline for the analysis, comparison, and visualization of the technological structures derived from national IOTs, i.e., the domestic supply chains described by matrices of technical coefficients that can be used to detect the role of different sectors in the propagation of a shock. The proposed pipeline has in our view two main advantages.

First, NMF provides a robust dimensionality reduction since it takes into account the inherent complexity of the data without altering the original ones. In our application, we extract three main archetypes of the technological structures of the 28 EU countries, describing any national structure as a mix of these three archetypes. On the one hand, that relevant reduction in the objects to handle (i.e., from 28 to 3) results particularly useful in informing policies when a promptly coordinated response to a common shock is needed, minimizing the computational effort. On the other hand, this approach allows us to capture the heterogeneity among national technological structures, analysing the mix of the archetypes among different countries, and thus offer a guide for the design of supranational policies. The low heterogeneity observed for the majority of the EU countries, which is aligned toward Archetype I, is a strong support for the adoption of common supranational policies, suggesting that a given measure would work similarly fashion across them and, at the same time, partially different, ad hoc, measures should be proposed for those countries where the other two archetypes prevail (Cyprus, Greece and Croatia).

Second, the archetypes provide a flexible tool for the application of different network analysis indicators and techniques, such as the centrality measures widely applied to identify the key sectors in the propagation of a shock. We exemplify this advantage through a shock propagation exercise that applies the unweighted random walk centrality by Blöchl et al. (2011) as representative of a general shock and then we adapt it to a real-world supply shock, i.e., the COVID-19 lockdown restrictions, proposing a weighted measure. These measures result in a ranking of the sectors in terms of shock propagation rapidity: higher is the centrality of the sector, more quickly the sector is affected by a supply shock occurred in the economy. Especially for the Archetype I, the comparison between the sectoral centrality profile of the two scenarios does not show marked differences. This suggests that for the majority of the EU countries, given their interconnected technological structure, the ranking of sectors resulting from the unweighted case can be used as a benchmark reference of a general supply shock affecting domestic supply chains.

For future work, it would be interesting to explore the temporal evolution of the domestic productive linkages of the EU countries and assess the impact of demand-side shocks, beside supply-side ones. Importantly, our proposed approach can be further investigated by explicitly introducing households to investigate induced effects of an expansion of the final demand, or conveniently adapted to consider imports and exports of an economy. Finally, other IOTs dataset could be utilised to evaluate the effectiveness of our proposal for other groups of countries, also extending the shock propagation scenarios.

8 Declaration of interests

The authors declare that they have no known competing financial interests or personal relationships that could have influenced the work reported in this paper.

References

Acemoglu, D., U. Akcigit, and W. Kerr (2015, July). Networks and the Macroeconomy: An Empirical Exploration. *Nber macroeconomics annual 30*(1), 273–335.

Acemoglu, D., V. M. Carvalho, A. Ozdaglar, and A. Tahbaz-Salehi (2012). The Network Origins of Aggregate Fluctuations. *Econometrica 80*(5), 1977–2016.

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

Argüelles, M., C. Benavides, and I. Fernández (2014, apr). A new approach to the identification of regional clusters: hierarchical clustering on principal components. *Applied Economics 46*(21), 2511–2519.

Baqaee, D. and E. Farhi (2020). Nonlinear production networks with an application to the covid-19 crisis. Working Paper 27281, National Bureau of Economic Research.

Battiston, S., D. D. Gatti, M. Gallegati, B. Greenwald, and J. E. Stiglitz (2012, aug). Liaisons dangereuses: Increasing connectivity, risk sharing, and systemic risk. *Journal of Economic Dynamics and Control 36*(8), 1121–1141.

Bazzana, D., J. J. Cohen, N. Golinucci, M. Hafner, M. Noussan, J. Reichl, M. V. Rocco, A. Sciullo, and S. Vergalli (2022). A multi-disciplinary approach to estimate the medium-term impact of covid-19 on transport and energy: A case study for italy. *Energy 238*, 122015.

Belhadi, A., S. Kamble, C. J. C. Jabbour, A. Gunasekaran, N. O. Ndubisi, and M. Venkatesh (2021). Manufacturing and service supply chain resilience to the covid-19 outbreak: Lessons learned from the automobile and airline industries. *Technological Forecasting and Social Change 163*, 120447.

Berry, M. W., M. Browne, A. N. Langville, V. P. Pauca, and R. J. Plemmons (2007, sep). Algorithms and applications for approximate nonnegative matrix factorization. *Computational Statistics & Data Analysis 52*(1), 155–173.

Bioucas-Dias, J. M. and J. M. P. Nascimento (2005, oct). Estimation of signal subspace on hyperspectral data. In L. Bruzzone (Ed.), *Image and Signal Processing for Remote Sensing XI*, pp. 191–198. SPIE.

Bisias, D., M. Flood, A. W. Lo, and S. Valavanis (2012). A survey of systemic risk analytics. *Annual Review of Financial Economics 4*(1), 255–296.

Bisot, V., R. Serizel, S. Essid, and G. Richard (2016, mar). Acoustic scene classification with matrix factorization for unsupervised feature learning. In *2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*, pp. 6445–6449. IEEE.

Blöchl, F., F. J. Theis, F. Vega-Redondo, and E. O. Fisher (2011, apr). Vertex centralities in input-output networks reveal the structure of modern economies. *Physical Review E 83*(4), 046127.

Bodnár, K., J. Le Roux, P. Lopez-Garcia, B. Szörfi, et al. (2020). The impact of covid-19 on potential output in the euro area. *Economic Bulletin Articles 7*.

Bollobás, B. (2001). *Random Graphs*. Cambridge University Press.

Bonaccorsi, G., F. Pierri, F. Scotti, A. Flori, F. Manaresi, S. Ceri, and F. Pammolli (2021). Socioeconomic differences and persistent segregation of italian territories during covid-19 pandemic. *Scientific Reports 11*(1), 1–15.

Bonadio, B., Z. Huo, A. A. Levchenko, and N. Pandalai-Nayar (2020). Global supply chains in the pandemic. Working Paper w27224, National Bureau of Economic Research.

Bonet-Morón, J., D. Ricciulli-Marín, G. J. Pérez-Valbuena, L. A. Galvis-Aponte, E. A. Haddad, I. F. Araújo, and F. S. Perobelli (2020). Regional economic impact of covid-19 in colombia: An input–output approach. *Regional Science Policy & Practice 12*(6), 1123–1150.

Bonfiglio, A., S. Coderoni, and R. Esposti (2022). Policy responses to covid-19 pandemic waves: Cross-region and cross-sector economic impact. *Journal of Policy Modeling*.

Borgatti, S. P. (2005, jan). Centrality and network flow. *Social Networks 27*(1), 55–71.

Brunet, J.-P., P. Tamayo, T. R. Golub, and J. P. Mesirov (2004, mar). Metagenes and molecular pattern discovery using matrix factorization. *Proceedings of the National Academy of Sciences 101*(12), 4164–4169.

Burgos, D. and D. Ivanov (2021). Food retail supply chain resilience and the covid-19 pandemic: A digital twin-based impact analysis and improvement directions. *Transportation Research Part E: Logistics and Transportation Review 152*, 102412.

Çakmaklı, C., S. Demiralp, S. Kalemli-Ozcan, S. Yesiltas, and M. A. Yildirim (2020). Covid-19 and emerging markets: an epidemiological model with international production networks and capital flows. *IMF Working Papers 2020(133).*

Carvalho, V. M. (2014, November). From Micro to Macro via Production Networks. *Journal of Economic Perspectives 28*(4), 23–48.

Carvalho, V. M. and A. Thabaz-Salehi (2019). Production Networks: A Primer. *Annual Review of Economics 11*(1), 635–663.

Cerina, F., Z. Zhu, A. Chessa, and M. Riccaboni (2015, July). World Input-Output Network. *PLoS ONE 10*(7), Article e0134025.

Chen, G., C. Xu, J. Wang, J. Feng, and J. Feng (2020, jun). Nonnegative matrix factorization for link prediction in directed complex networks using PageRank and asymmetric link clustering information. *Expert Systems with Applications 148*, 113290.

Chenery, H. B. and T. Watanabe (1958). International comparisons of the structure of production. *Econometrica 26*, 487–521.

Chu, M., F. Diele, R. Plemmons, and S. Ragni (2004). *Optimality, computation and interpretation of nonnegative matrix factorizations.* SIAM Journal of Matrix Analysis and Applications.

Cichocki, A., R. Zdunek, and S. Amari (2008). Nonnegative Matrix and Tensor Factorization [Lecture Notes]. *IEEE Signal Processing Magazine 25*(1), 142–145.

Cichocki, A., R. Zdunek, A. H. Phan, and S. Amari (2009, sep). *Nonnegative Matrix and Tensor Factorizations.* John Wiley & Sons, Ltd.

Cottafava, D., M. Gastaldo, F. Quatraro, and C. Santhiá (2022). Modeling economic losses and greenhouse gas emissions reduction during the covid-19 pandemic: Past, present, and future scenarios for italy. *Economic Modelling 110*, 105807.

De Benedictis, L., S. Nenci, G. Santoni, L. Tajoli, and C. Vicarelli (2014, sep). Network analysis of world trade using the baci-cepii dataset. *Global Economy Journal 14*(03n04), 287–343.

De Benedictis, L. and L. Tajoli (2011, sep). The world trade network. *The World Economy 34*(8), 1417–1454.

del Rio-Chanona, R. M., P. Mealy, A. Pichler, F. Lafond, and J. D. Farmer (2020). Supply and demand shocks in the covid-19 pandemic: An industry and occupation perspective. *Oxford Review of Economic Policy 36*(Supplement_1), S94–S137.

Díaz, B., L. Moniche, and A. Morillas (2006, September). A Fuzzy clustering approach to the key sectors of the Spanish economy. *Economic Systems Research 18*(3), 299–318.

Dietzenbacher, E. and M. L. Lahr (2013). Expanding extractions. *Economic Systems Research 25*(3), 341–360.

Dietzenbacher, E. and R. E. Miller (2015). Reflections on the inoperability input–output model. *Economic Systems Research 27*(4), 478–486.

Dietzenbacher, E. and I. Romero (2007). Production chains in an interregional framework: Identification by means of average propagation lengths. *International Regional Science Review 30*(4), 362–383.

Dietzenbacher, E., B. van Burken, and Y. Kondo (2019). Hypothetical extractions from a global perspective. *Economic Systems Research 31*(4), 505–519.

Ding, C., T. Li, and M. I. Jordan (2008, dec). Nonnegative Matrix Factorization for Combinatorial Optimization: Spectral Clustering, Graph Matching, and Clique Finding. In *2008 Eighth IEEE International Conference on Data Mining*, pp. 183–192. IEEE.

Dingel, J. I. and B. Neiman (2020). How Many Jobs Can be Done at Home? Working Paper 26948, National Bureau of Economic Research.

Eisenberg, L. and T. H. Noe (2001, feb). Systemic Risk in Financial Systems. *Management Science 47*(2), 236–249.

Elliott, M., B. Golub, and M. O. Jackson (2014). Financial networks and contagion. *American Economic Review 104*(10), 3115–53.

Elliott, R. (2021). Supply chain resilience report 2021. Technical report, Business Continuity Institute.

European Commission (2020). *Communication from the Commission to the European Parliament, the European Council, the Council, the European Central Bank, the European Investment Bank and the Eurogroup: Coordinated economic response to the COVID-19 Outbreak.*

Fadinger, H., J. Schymik, et al. (2020). The effects of working from home on covid-19 infections and production a macroeconomic analysis for germany. *Covid Economics 9*(24), 107–139.

Fagiolo, G., J. Reyes, and S. Schiavo (2008). On the topological properties of the world trade web: A weighted network analysis. *Physica A: Statistical Mechanics and its Applications 387*(15), 3868–3873.

Frigyesi, A. and M. Höglund (2008, jan). Non-negative matrix factorization for the analysis of complex gene expression data: Identification of clinically relevant tumor subtypes. *Cancer Informatics 6*, 275–292.

Gabaix, X. (2011). The Granular Origins of Aggregate Fluctuations. *Econometrica 79*(3), 733–772.

Gai, P. and S. Kapadia (2010). Contagion in financial networks. *Proceedings of the Royal Society A: Mathematical, Physical and Engineering Sciences 466*(2120), 2401–2423.

Giammetti, R., L. Papi, D. Teobaldelli, and D. Ticchi (2020). The italian value chain in the pandemic: the input–output impact of covid-19 lockdown. *Journal of Industrial and Business Economics 47*(3), 483–497.

Giammetti, R., A. Russo, and M. Gallegati (2020). Key sectors in input–output production networks: An application to brexit. *The World Economy 43*(4), 840–870.

Gillis, N. (2011). *Nonnegative matrix factorization : complexity, algorithms and applications.* Ph. D. thesis, Université Catholique de Louvain.

Gillis, N. (2014). The why and how of nonnegative matrix factorization.

Glasserman, P. and H. P. Young (2015). How likely is contagion in financial networks? *Journal of Banking & Finance 50*, 383–399.

Golan, M. S., L. H. Jernegan, and I. Linkov (2020). Trends and applications of resilience analytics in supply chain modeling: systematic literature review in the context of the covid-19 pandemic. *Environment Systems and Decisions 40*, 222–243.

Govindan, K., H. Mina, and B. Alavi (2020). A decision support system for demand management in healthcare supply chains considering the epidemic outbreaks: A case study of coronavirus disease 2019 (covid-19). *Transportation Research Part E: Logistics and Transportation Review 138*, 101967.

Guan, D., D. Wang, S. Hallegatte, S. J. Davis, J. Huo, S. Li, Y. Bai, T. Lei, Q. Xue, D. Coffman, D. Cheng, P. Chen, X. Liang, B. Xu, X. Lu, S. Wang, K. Hubacek, and P. Gong (2020, jun). Global supply-chain effects of COVID-19 control measures. *Nature Human Behaviour 4*(6), 577–587.

Guerrieri, V., G. Lorenzoni, L. Straub, and I. Werning (2020, April). Macroeconomic implications of covid-19: Can negative supply shocks cause demand shortages? Working Paper 26918, National Bureau of Economic Research.

Haddad, E. A., F. S. Perobelli, I. F. Araújo, and K. S. Bugarin (2021). Structural propagation of pandemic shocks: an input–output analysis of the economic costs of covid-19. *Spatial Economic Analysis 16*(3), 252–270.

Haren, P. and D. Simchi-Levi (2020). How coronavirus could impact the global supply chain by mid-march. *Harvard Business Review 28*.

Hastie, T., R. Tibshirani, and J. Friedman (2009). *The Elements of Statistical Learning*. Springer-Verlag New York Inc.

Hirschman, A. O. (1958). *The strategy of economic development*. Yale University Press.

Hutchins, L. N., S. M. Murphy, P. Singh, and J. H. Graber (2008, oct). Position-dependent motif characterization using non-negative matrix factorization. *Bioinformatics 24*(23), 2684–2690.

Inoue, H. and Y. Todo (2020). The propagation of economic impacts through supply chains: The case of a mega-city lockdown to prevent the spread of covid-19. *PLoS ONE 15*(9), Article e0239251.

Istat (2022). Rapporto sulla competitività dei settori produttivi. edizione 2022. Letture statistiche - temi., Italian National Institute of Statistics.

Ivanov, D. (2020a). Predicting the impacts of epidemic outbreaks on global supply chains: A simulation-based analysis on the coronavirus outbreak (covid-19/sars-cov-2) case. *Transportation Research Part E: Logistics and Transportation Review 136*, 101922.

Ivanov, D. (2020b, may). Viable supply chain model: integrating agility, resilience and sustainability perspectives—lessons from and thinking beyond the COVID-19 pandemic. *Annals of Operations Research*, 1–21.

Jackson, M. O. (2011). *Social and Economic Networks*. Princeton University Press.

Jensen, R. C., J. H. Dewhurst, G. R. West, and G. J. Hewings (1991). On the concept of fundamental economic structure. *Regional Input-Output Modeling: New Development and Interpretations, Avebury, Sydney*, 228–49.

Jha, P. K., S. Ghorai, R. Jha, R. Datt, G. Sulapu, and S. P. Singh (2021). Forecasting the impact of epidemic outbreaks on the supply chain: modelling asymptomatic cases of the covid-19 pandemic. *International Journal of Production Research*, 1–26.

Johnson, R. and D. Wichern (2014). *Applied Multivariate Statistical Analysis: Pearson New International Edition* (Sixth ed.). Pearson Education Limited.

Kagawa, S., S. Okamoto, S. Suh, Y. Kondo, and K. Nansai (2013, jul). Finding environmentally important industry clusters: Multiway cut approach using nonnegative matrix factorization. *Social Networks 35*(3), 423–438.

Kanemoto, K., T. Hanaka, S. Kagawa, and K. Nansai (2018, jul). Industrial clusters with substantial carbon-reduction potential. *Economic Systems Research 31*(2), 248–266.

Kenan, N. and A. Diabat (2022). The supply chain of blood products in the wake of the covid-19 pandemic: Appointment scheduling and other restrictions. *Transportation Research Part E: Logistics and Transportation Review 159*, 102576.

Kim, D., S. Sra, and I. S. Dhillon (2007, apr). Fast Newton-type Methods for the Least Squares Nonnegative Matrix Approximation Problem. In *SIAM International Conference on Data Mining (SDM)*.

Koks, E. E., L. Carrera, O. Jonkeren, J. C. Aerts, T. G. Husby, M. Thissen, G. Standardi, and J. Mysiak (2016). Regional disaster impact analysis: comparing input–output and computable general equilibrium models. *Natural Hazards and Earth System Sciences 16*(8), 1911–1924.

Koks, E. E. and M. Thissen (2016). A multiregional impact assessment model for disaster analysis. *Economic Systems Research 28*(4), 429–449.

Koren, M. and R. Pető (2020). Business disruptions from social distancing. *PLoS ONE 15*(9), Article e0239113.

Lee, D. D. and H. S. Seung (1999, oct). Learning the parts of objects by non-negative matrix factorization. *Nature 401*(6755), 788–791.

Lee, D. D. and H. S. Seung (2000). Algorithms for Non-negative Matrix Factorization. *Proceedings of the 13th International Conference on Neural Information Processing Systems*, 535–541.

Lenzen, M., M. Li, A. Malik, F. Pomponi, Y.-Y. Sun, T. Wiedmann, F. Faturay, J. Fry, B. Gallego, A. Geschke, et al. (2020). Global socio-economic losses and environmental gains from the coronavirus pandemic. *PLoS One 15*(7), Article e0235654.

Leontief, W. W. (1936, August). Quantitative Input and Output Relations in the Economic Systems of the United States. *The Review of Economics and Statistics 18*(3), 105–125.

Leontief, W. W. (1951). *The Structure of american Economy, 1919-1939: An Empirical Application of Equilibrium Analysis* (2ND ED. ed.). Oxford University Press.

Li, W., J. Xie, M. Xin, and J. Mo (2018, January). An overlapping network community partition algorithm based on semi-supervised matrix factorization and random walk. *Expert Systems with Applications 91*, 277–285.

Lin, C. (2007, oct). Projected Gradient Methods for Nonnegative Matrix Factorization. *Neural Computation 19*(10), 2756–2779.

Mandel, A. and V. Veetil (2020). The economic cost of covid lockdowns: an out-of-equilibrium analysis. *Economics of Disasters and Climate Change 4*(3), 431–451.

Marron, J. S. and A. M. Alonso (2014, January). Overview of object oriented data analysis. *Biometrical Journal 56*(5), 732–753.

Masuda, N., M. A. Porter, and R. Lambiotte (2017, nov). Random walks and diffusion on networks. *Physics Reports 716-717*, 1–58.

McKibbin, W. and R. Fernando (2021). The global macroeconomic impacts of covid-19: Seven scenarios. *Asian Economic Papers 20*(2), 1–30.

Miller, R. E. and P. D. Blair (2009). *Input-output analysis: foundations and extensions.* Cambridge University Press.

Newman, M. (2010). *Networks: An Introduction.* Oxford University Press.

OECD (2020, sep). *OECD Economic Outlook, Interim Report September 2020.* OECD Publishing.

Okuyama, Y. (2007). Economic modeling for disaster impact analysis: past, present, and future. *Economic Systems Research 19*(2), 115–124.

Okuyama, Y. (2014). Disaster and economic structural change: case study on the 1995 kobe earthquake. *Economic Systems Research 26*(1), 98–117.

Okuyama, Y. and J. R. Santos (2014). Disaster impact and input–output analysis. *Economic Systems Research 26*(1), 1–12.

Okuyama, Y. and K. D. Yu (2019). Return of the inoperability. *Economic Systems Research 31*(4), 467–480.

Oosterhaven, J. and K. Polenske (2009). *Modern regional input-output and impact analyses, Handbook of Regional Growth.* Edward Elgar Publishing Limited.

Owen, A. B. and P. O. Perry (2009, jun). Bi-cross-validation of the SVD and the nonnegative matrix factorization. *The Annals of Applied Statistics 3*(2), 564–594.

Paatero, P. and U. Tapper (1994, jun). Positive matrix factorization: A non-negative factor model with optimal utilization of error estimates of data values. *Environmetrics 5*(2), 111–126.

Page, L. (2001). Method for node ranking in a linked database. USA Patent 6,285,999 (September 4, 2001).

Papanikolaou, D. and L. D. Schmidt (2020). Working remotely and the supply-side impact of covid-19. Working Paper 27330, National Bureau of Economic Research.

Paul, S. K., P. Chowdhury, R. K. Chakrabortty, D. Ivanov, and K. Sallam (2022). A mathematical model for managing the multi-dimensional impacts of the covid-19 pandemic in supply chain of a high-demand item. *Annals of Operations Research*, 1–46.

Pedauga, L., F. Sáez, and B. L. Delgado-Márquez (2021). Macroeconomic lockdown and smes: the impact of the COVID-19 pandemic in Spain. *Small Business Economics*, 1–24.

Pedregosa, F., G. Varoquaux, A. Gramfort, V. Michel, B. Thirion, O. Grisel, M. Blondel, P. Prettenhofer, R. Weiss, V. Dubourg, J. Vanderplas, A. Passos, D. Cournapeau, M. Brucher, M. Perrot, and E. Duchesnay (2011). Scikit-learn: Machine Learning in Python. *Journal of Machine Learning Research 12*, 2825–2830.

Picek, O. (2020). Spillover effects from next generation eu. *Intereconomics 55*(5), 325–331.

Pichler, A. and J. D. Farmer (2021). Simultaneous supply and demand constraints in input–output networks: the case of Covid-19 in Germany, Italy, and Spain. *Economic Systems Research*, 1–21.

Pomponi, F., M. Li, Y.-Y. Sun, A. Malik, M. Lenzen, G. Fountas, B. D'Amico, O. Akizu-Gardoki, and M. Luque Anguita (2021). A novel method for estimating emissions reductions caused by the restriction of mobility: The case of the covid-19 pandemic. *Environmental Science & Technology Letters 8*(1), 46–52.

Rasmussen, P. N. (1956). *Studies in inter-sectoral relations*. E. Harcks.

Reyes, J., S. Schiavo, and G. Fagiolo (2008). Assessing the evolution of international economic integration using random walk betweenness centrality: The cases of east asia and latin america. *Advances in Complex Systems 11*(05), 685–702.

Schiavo, S., J. Reyes, and G. Fagiolo (2010). International trade and financial integration: a weighted network analysis. *Quantitative Finance 10*(4), 389–399.

Schnabl, H. (1995). The subsystem—mfa: A qualitative method for analyzing national innovation systems—the case of germany. *Economic Systems Research 7*(4), 383–396.

Simpson, D. and J. Tsukui (1965). The fundamental structure of input-output tables, an international comparison. *The Review of Economics and Statistics 47*(4), 434–446.

Smaragdis, P., C. Fevotte, G. J. Mysore, N. Mohammadiha, and M. Hoffman (2014, may). Static and Dynamic Source Separation Using Nonnegative Factorizations: A unified view. *IEEE Signal Processing Magazine 31*(3), 66–75.

Smolyak, A., G. Bonaccorsi, A. Flori, F. Pammolli, and S. Havlin (2021). Effects of mobility restrictions during covid19 in italy. *Scientific reports 11*(1), 1–15.

Sonis, M. and G. J. Hewings (1991). *Fields of influence and extended input-output analysis: a theoretical account*, pp. 141–158. Aldershot: Avebury.

Sonis, M. and G. J. Hewings (1992). Coefficient change in input–output models: theory and applications. *Economic Systems Research 4*(2), 143–158.

Sonis, M., G. J. D. Hewings, and J. Guo (1996). Sources of structural change in input–output systems: A field of influence approach. *Economic Systems Research 8*(1), 15–32.

Spelta, A., A. Flori, F. Pierri, G. Bonaccorsi, and F. Pammolli (2020). After the lockdown: simulating mobility, public health and economic recovery scenarios. *Scientific Reports 10*(1), 1–13.

Squires, S., A. Prügel-Bennett, and M. Niranjan (2017, aug). Rank selection in nonnegative matrix factorization using minimum description length. *Neural Computation 29*(8), 2164–2176.

Steenge, A. E. and M. Bočkarjova (2007). Thinking about imbalances in post-catastrophe economies: an input–output based proposition. *Economic Systems Research 19*(2), 205–223.

Tan, V. Y. F. and C. Fevotte (2013, jul). Automatic Relevance Determination in Nonnegative Matrix Factorization with the β-Divergence. *IEEE Transactions on Pattern Analysis and Machine Intelligence 35*(7), 1592–1605.

Ten Raa, T. (2014). *The Economics of Input-Output Analysis*. Cambridge University Press.

Ten Raa, T. (2017). *Handbook of input–output analysis*. Edward Elgar Publishing.

Thakur, S. K. (2008). Identification of temporal fundamental economic structure (FES) of India: an input–output and cross-entropy analysis. *Structural Change and Economic Dynamics 19*(2), 132–151.

Thakur, S. K. (2011). Fundamental economic structure and structural change in regional economies: a methodological approach. *Région et Développement 33*, 9–38.

Timmer, M., B. Los, R. Stehrer, and G. de Vries (2016). An anatomy of the global trade slowdown based on the WIOD 2016 release. WorkingPaper 162, Groningen Growth and Development Centre, University of Groningen.

Timmer, M. P., E. Dietzenbacher, B. Los, R. Stehrer, and G. J. de Vries (2015, April). An Illustrated User Guide to the World Input-Output Database: the Case of Global Automotive Production. *Review of International Economics 23*(3), 575–605.

Verschuur, J., E. E. Koks, and J. W. Hall (2021). Observed impacts of the covid-19 pandemic on global trade. *Nature Human Behaviour 5*(3), 305–307.

Villani, D. and M. Fana (2021). Productive integration, economic recession and employment in europe: an assessment based on vertically integrated sectors. *Journal of Industrial and Business Economics 48*(2), 137–157.

Wang, S. and A. Huang (2017, jul). Penalized nonnegative matrix tri-factorization for co-clustering. *Expert Systems with Applications 78*, 64–73.

Wu, X. and Y. Jiang (2011, June). Sectoral role change in transition China: a network analysis from 1990 to 2005. *Applied Economics 44*(21), 2699–2715.

Xia, Y., D. Guan, A. E. Steenge, E. Dietzenbacher, J. Meng, and D. Mendoza Tinoco (2019). Assessing the economic impacts of IT service shutdown during the york flood of 2015 in the UK. *Proceedings of the Royal Society A 475*(2224), Article 20180871.

Xing, L., Q. Ye, and J. Guan (2016). Spreading Effect in Industrial Complex Network Based on Revised Structural Holes Theory. *PLoS ONE 11*(5), Article e0156270.

Zhang, J., L. Wei, X. Feng, Z. Ma, and Y. Wang (2008). Pattern expression nonnegative matrix factorization: Algorithm and applications to blind source separation. *Computational Intelligence and Neuroscience 2008*, 1–10.