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Economic vulnerabilities in Italy

A network analysis using similarities in sectoral employment

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Abstract

This article presents an original spatial methodology based on a network analysis approach in order to identify and to track spatial similarities among economic activities as well as to analyse their interdependence. Traditionally, such interdependence is analysed using input-output matrices (IO) that track economic flows across sectors. However, models based on IO do not allow to analyse spatial interdependence. In our approach, instead, we make use of local employment patterns. In particular, using sectoral employment of 8091 Italian municipalities across 18 economic activities, our approach allows to identify spatial inter-linkages in terms of employment patterns. By comparing such local employment patterns, our methodology shows inter-linkages among activities, which are important for understanding the transmission of exogenous shocks. Our analysis highlights similarities among economic activities, and allows to identify central activities (hubs) and their relationship with each other. Moreover, simulating the spread of an exogenous shock through the economic structure allows us to identify important activities not only in economic terms but also in terms of centrality and connectivity.

Key words: Network analysis, local employment patterns, business cycles, financial sector, spatial economic analysis

JEL codes: C19, C67, E32, R12, R15

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1 Introduction

Linkages across industries and economic sectors are typically analysed using input-output (IO) tables that document the supply and demand of goods and services in an economic system for a particular period. It provides a detailed picture of the structure of the economy and a basis for analysing inter-sectoral relationships. Recently, such IO tables have been used to analyse and examine the network structure of economies and the transmission mechanism of shocks, using advancements in the "science of networks" developed to highlight various dimensions of linkages across sectors (Acemoglu *et al.*, 2012, 2015).

The study of networks has had a long history in mathematics and science (Newman *et al.*, 2006). One of the most important findings, popularized by Barabási and his team, is that real networks behave differently from traditional assumptions of network theory (Albert and Barabási, 2002). Indeed, modern network research shows that the majority of nodes of real networks has a relatively low connectivity, and, by contrast, there exists some nodes with very high connectivity, also called hubs.

Identifying linkages between industries, sectors or economic activities following a network approach becomes highly pertinent when identifying and tracking linkages in the case of an exogenous shock. It also allows to be more precise in estimating the intensity with which a shock is transmitted through the network of sectors, taking into account the position of each activity in the network system. This can have substantial policy implications.

Analysing the network structure of industries and sectors on the basis of IO tables has, however, a significant shortcoming: It does not allow to identify the spatial linkages that exist within an economy. Indeed, IO only reflect aggregate linkages, sub-national differences in shock transmission and regional linkages cannot be analysed. In countries and economies with large regional differences in income and employment, however, such spatial inter-linkages might be important and reveal important transmission mechanism of both domestic and international shocks that cannot be detected by analysing IO tables alone.

The following paper offers a new methodology, applying the tools of network analysis to sub-national information on the employment structure in Italy. Specifically, sectoral employment data for more than 8000 Italian municipalities is being used to detect network linkages, using sectoral similarities across municipalities. Estimating the minimum spanning tree in order to detect the connectivity across sectors in this sector allows to identify hubs and the degree of connectivity across sectors. In a second step we use our estimated network structure to analyse the transmission of sectoral shocks across the economy, focusing on shocks on the hubs that our method has allowed to identify.

The method suggested here has two major advantages over existing studies on the network structure of economies: As indicated, it explicitly takes interdependence resulting from spatial linkages into account. Moreover, it allows an analysis of network interdependence even in those cases where IO tables are not readily available. This latter may be particularly important in countries where data collection is rare and incomplete. Whereas most national account and labour force information is often available at the sub-national (e.g. regional) level, IO tables require a distinct effort and are typically not updated more often than every five years, even in countries with well-developed statistical agencies.

Our article is structured as follows. First, we present an overview of network analysis in economics. Then, we discuss our methodology, presenting first some theoretical concepts. In section four we will apply our methodology to Italy by using the local employment of 8091 municipalities across 18 economic activities. Finally, based on the result of this application, we evaluate numerically the effects of a shock, highlighting the trajectory of this shock and its cascading impact on different sectors. A final section concludes.

2 Literature review

Representing an economy as a structure of interlinked sectors is not new. Even before national accounts became the norm, Leontief (1936) developed the first input-output table of the US economy in order to map patterns of trade and interrelations between different economic sectors. Leontief’s input-output (IO) model is an adaptation of the neoclassical theory of general equilibrium to the empirical analysis of interdependence between activities (Leontief, 1966). “Input-output analysis is like general-equilibrium theory in that it encompasses all products and industries, rather than singling out one or a few for study and relegating the others to the pound of *ceteris paribus*. Thus, the impact of a change in any corner of the economy can conceivably find its way via indirect effects through the input-output chart to every other industry” (Christ, 1955, p. 143). Combined with the new opportunities that the development of information technologies offered in during the 1950s and 1960s, these IO-tables would therefore encourage the expansion of complex models of economic analysis. This methodology allowed to quantify the effect of some real changes, anticipated or hypothetical, relating to an economy.

In recent years, scientists from a range of fields – including mathematics, physics, computer science, sociology, and biology – have developed a new “science of networks” that allows to specify another dimension of linkages in a range of scientific areas. The analysis of networks has a long history in mathematics and science (Newman *et al.*, 2006) but has recently received a major boost due to the significantly increased availability of network data resources. One of the most important findings, popularized by Barabási and his team, is that real networks behave very differently from traditional assumptions about networks.

Traditionally, real networks were supposed to have a majority of nodes of about the same number of connections around an average. This is typically modeled by random graphs. However, modern network research shows that the majority of nodes of real networks have only few connections, with some nodes – dubbed “hubs” – being characterised by a high connectivity. This characteristics – called “scale-free” – can be found in many real networks from biological to social networks.

Such network specificities have consequences for the transmission of exogenous shocks to an (economic) system. “When a network acts as a transportation system, a local failure shifts loads to other nodes. If the extra load is negligible, the system can seamlessly absorb it, and the failure goes unnoticed. If, however, the extra load is too much for the neighboring nodes, they will too tip and redistribute the load to their neighbors. In no time, we are faced with a cascading event, whose magnitude depends on the position and the capacity

of the nodes that failed initially” (Barabási, 2015). Their impact can travel along the network’s links and affect other nodes, such as consumers and firms. From an economist’s perspective, therefore, accounting for the patterns of (economic and social) interactions by making use of network theory can lead to an improved understanding of economic dynamics, including product adoption, financial contagions and unemployment dynamics.

There are two prominent areas for analyzing social networks: developing economics and labor economics. In developing economies, for instance, analysing social networks help to portray the importance of informal and social interactions: In these countries, relations are “not relying on formal contracts or exogenous institutions, but relying heavily on social interactions (see the chapters by Breza, 2016; Mobius and Rosenblat, 2016; Munshi, 2016). In labour economics, on the other hand, networks play an important role in analysing the access to (job) opportunities. Family and friends, for instance, play an important role in shaping the decision of individuals to take up education, which occupation to choose and how much effort to put into one’s job (search). Analysing network patterns of (social) interaction, therefore, can help to disentangle information spillovers from norms (Jackson, 2008).

Besides these two areas of application, economists have shown particular interest in financial networks as well as business cycle dynamics arising from micro-economic risk and interdependence in an economy. Network analysis helps to understand the indirect effects of shocks at the micro-economic level and their transmissions to the macro-economy (see the chapters by Acemoglu *et al.*, 2016; Cabrales *et al.*, 2016). Hence, studying networks over the past couple of decades has helped economists to “identify the impact of network structure on economic behaviors, and as a result is reshaping some policies, as well as testing and refining theory” (Jackson, 2008). It helps, also, to highlight another kind of dependency relations which could be helpful to anticipate the trajectory of an exogenous stimulus and its damaging cascades.

Making use of recent progress in this area, we will provide a methodology that is based on two concepts: scale free networks and minimum spanning trees. The latter, which is a technique known in graph theory, will allow us to identify a hierarchical structure of the economic system of a country. The goal will be to represent a country’s economy as a network, with the nodes representing the sectors or economic activities and the vertices (links between the nodes) accounting for spatial similarities in the allocation of labor. Our approach is micro-founded because we will obtain our results by analyzing sectoral employment at the local (municipal) level. Each node (city) is characterised by the allocation of employment across different economic activities (following Carlei and Nuccio, 2014, who use a similar approach). We then calculate an Euclidean distance between economic activities in order to capture similarities across nodes regarding the pattern allocation of local resources. Finally we define the indexed hierarchy (network) between the sectors (nodes) based on the distance (similarity). Using this topological map of the economic structure built on similarities of local employment patterns, we will analyse the transmission of a shock through the network using a first order auto-regressive spatial model (LeSage, 1999). This will allow us to evaluate the spread of a sector-specific shock through the first-order neighborhoods.

3 Methodological framework

How do we estimate spatial linkages? In order to present our methodology for estimating spatial linkages we start by discussing some theoretical concepts and then present methodological aspects.

3.1 Theoretical concepts

Analyzing an economy as a network structure allows to estimate the interdependence among economic activities. In particular, the presence of interconnections across economic activities is a crucial issue in order to determine the effects of exogenous shocks. For instance, Acemoglu *et al.* (2012) show that micro-economic shocks at the level of individual sectors may propagate through the economy, affecting other sectors or activities, and generate sizable aggregate effects. They argued that the extent of propagation of idiosyncratic shocks and their role in aggregate fluctuations depend on the structure of interactions between different sectors or activities.

Our methodology is based on two network concepts: (1) scale-free networks and (2) minimum spanning trees (MST). We will prepare the database using the scale-free network and the MST in order to present inter-linkages among an economic activities. The literature on complex networks defines scale-free networks on the base of its connectivity distribution $P(k)$, which explains the probability that a node in the network is connected to k other nodes. In contrast to random networks characterized by a $P(k)$ that shows a peak at an average k and decay exponentially for large k (each node has approximately the same number of links), many systems belong to scale-free networks, for which $P(k)$ decays as a power law (i.e. $P(k) = k^{-\gamma}$), free of a characteristic scale (Barabási and Albert, 1999). The power law distribution describes systems in which a few nodes (hubs) dominate. Examples for scale-free networks can be found in social and communication connection patterns (Albert and Barabási, 2000; Barabási *et al.*, 2000; Barabási and Bonabeau, 2003). They are also used to describe metabolic networks in different micro-organisms (Jeong *et al.*, 2000) or as a support to policymakers to suggest interesting policy guidelines aimed at eradicating an epidemic due to viruses (Dezso and Barabási, 2002).

An important property of scale-free network is their robustness to random failures and an increased vulnerability to coordinated attacks. This robustness (vulnerability) is rooted in their inhomogeneous connectivity distribution: since the majority of nodes have only few links because of power law distribution, any attack against them does not alter the path structure of the remaining nodes, and thus has no impact on the overall network topology. An informed agent that attempts to deliberately introduce an exogenous shock into the network will preferentially target the most connected nodes (hubs) (Albert and Barabási, 2000). Once a hub has been affected by a shock it will pass it onto numerous other nodes and its effects will spread throughout the entire system or a part of it because they are connected to many other nodes (Barabási and Bonabeau, 2003).

This kind of network is interesting because the behavior of a complex network seems to act in predictable ways when it undergoes an exogenous shock. In other words, a network containing hubs, or nodes with a large number of links,

seems to be extremely vulnerable to coordinated attacks because of their inhomogeneous topology (Barabási and Bonabeau, 2003). Analyzing an economic structure as a network and its topological properties in terms of the links across industries is interesting to the extent that similarities with scale-free networks might be detected, implying dynamics spreading over economic sectors. This feature is analytically demonstrated by combining graph theoretical concepts with percolation theory (Schwartz *et al.*, 2002).

Our work is also related to studies on the theoretical concept of minimum spanning trees (MST), a graph that connects all the vertices in a graph without forming any loop over the shortest path (Bonanno *et al.*, 2004). In our application we follow Mantegna (1999) who finds a topological arrangement of equities in financial markets by using a correlation based model in describing a network's shape and topology through an MST, as a specialized filtering procedure that allows them to investigate co-occurrences of a set of highly capitalized stocks, i.e. some of these stocks act as hubs of a local cluster. The underlying hypothesis of this procedure is that time series of financial market returns reflect information about the economic sector of the activity of a company, once they are grouped in clusters of nodes over the network (Bonanno *et al.*, 2004).

3.2 Methodological aspects

Against this theoretical background we develop a methodology in order to identify a hierarchical economic structure by specifying which economic activities play the role of a hub. This entails in identifying the most important activities able to affect others in spreading external solicitations, once sectoral interrelations have been analysed. Using the approach developed by Mantegna (1999), we define a new metric, building links among activities, in order to explore the structure of the economy and the related activities which eventually act as a hub.

The basic assumption of our new metric is that the urban morphology of the factor endowment (labor) for each sector is a proxy of the local production system. This point of view allows us to analyze each city as an urban pattern whose morphology is described in terms of its sectoral allocation of employment (Carlei and Nuccio, 2014). Our new metric measures the closeness among the sectors that constitute the nodes of a network where links are represented by the similarity of urban patterns in a Euclidean space. Our methodology help us to define the role of each sector or economic activity in the whole economy and the structural interdependence that emerges from local patterns of industrial co-agglomeration (Carlei and Nuccio, 2014).

When a link exists between two nodes (sectors) it means that they have a similar industrial structure as measured by their sectoral allocation of employment (represented by their Euclidean distance). The more the relative industrial relevance of a particular sector is similar to the same sector in another city, the closer the two sectors will be in the network. In other words, our assumption is that the morphology of the resources allocation in each activity (number of employees) is a proxy of the local production system. The existence of a link between two activities emerges from a similarity between them in terms of patterns of labor factor locally employed. Therefore, a highly connected activity is an activity that from a spatial point of view, in terms of number of employees

in each city, has a relative industrial relevance similar to its neighbors in the whole regions under investigation.

There are two extreme cases. On the one hand, an economic activity that is a hub could be the main economic activity of an industrial district where, following agglomeration economies, all the activities that constitute satellite activities are present locally (economic activities connected by a link). On the other hand, a hub could be a sector or activity that is similar to others, and therefore linked to them, due to the lack of an industrial relevance across the region (i.e. a very low number of employees on much of the municipalities considered).

This network structure is configured through a MST, i.e. the path is presented after a pruning process of a connected graph. This allows us to obtain a network configuration which indicates the most likely path of a shock propagation. Our objective is to find connection patterns across economic activities. This network-based approach is particularly appropriate when highly connected sectors (hubs) emerge on the topological map. In such a case a micro-economic shock will propagate through the inter-sectoral network structure generating larger and aggregate fluctuations (Acemoglu *et al.*, 2012).

Regarding our paper, we will define cities as geographical samples and the number of employees for each activity as a feature. Both samples and features can be employed at different levels of aggregation: the first one can be municipality, province, region or country; the second one can refer to different economic activities and various classifications, consistently with the number of digits for each industry. This allows us to associate each city with a pattern whose morphology is described in terms of allocation of resources employed in each activity (factor endowment). From this hypothesis we can build the network. In our analysis the nodes of the network are the economic activities and the links represent their closeness in the Euclidean space in terms of urban patterns (see equation (1)). In other words, spatial similarities between two activities indicate the existence of a spatial interdependence between them.

Our network-based approach takes into account a data set obtained from matrix X , whose entries $x_{i,j}$ are i -samples of the local economies (municipalities) and j -features of the employees' numbers for each industry. We re-scaled X into a new matrix Y whose entries $y_{i,j}$ are defined as:

$$y_{i,j} = \frac{e^{\delta_{i,j}}}{1 + e^{\delta_{i,j}}} \quad (1)$$

with

$$\delta_{i,j} = \alpha_i + \beta_i \cdot x_{i,j} \quad (2)$$

where

$$\alpha_i = \frac{1}{\max_j x_{i,j}} \quad (3)$$

and

$$\beta_i = \frac{\min_j x_{i,j}}{\max_j x_{i,j} - \min_j x_{i,j}} \quad (4)$$

In equations (3) and (4) α_i and β_i are the two vectors of parameters for the logistic function to re-scale matrix X by rows in order to preserve the key properties of the local distribution of employees across the different industries

for each sample. This way, each sample is represented by a pattern whose properties capture how the labour factor is locally allocated across activities (Carlei and Nuccio, 2014; Carlei *et al.*, 2016).

In order to draw a detailed network maps that highlights spatial interdependence across activities and their role in spreading an external solicitation, an indexed hierarchy between industries needs to be determined in a unique way (Mantegna and Stanley, 2000). This can be achieved setting up an MST Bonanno *et al.* (2004) as it can be shown that a one-to-one relationship exists between an indexed hierarchy and an ultrametric set (Rammal *et al.*, 1986). The spanning tree of the shortest length connecting the n activities is associated with the distance matrix D , i.e. the Euclidean distance $d_{i,j}$ between pairs of normalized activities y_i and y_j . How to construct an MST is well known in multivariate analysis (Mantegna and Stanley, 2000).

Once the topological map of the network is defined, it is necessary to identify the centrality of each sector in order to select nodes that play a crucial role because they are deeply connected. Such nodes are highly interdependent and, accordingly, play a crucial role in spreading an external solicitation throughout the network. In the following, we will look specifically at an application of this methodology to Italy in order to identify the pivot sectors and the role they have played in the most recent crisis.

4 A study case: Italy

In this section we present an application of the above mentioned methodology to the Italian employed population organized in 18 economic activities according to the ATECO 2007 2-digit classification and across 8091 Italian municipalities.¹ The data set gathers the overall number of the Italian municipalities, covering therefore the entire country with reference to the year 2011.²

As a result, the matrix $X_{i,j}$ has $i = 1, \dots, N = 8091$ municipalities and $j = 1, \dots, n = 18$ economic activities. Following this approach, relevant information will be extracted from the raw data applying the following three-steps procedure:

1. The original data set (number of local employees in each an economic activity) is normalized by rows in order to represent each sample as a pattern whose properties capture how the labor factor is locally allocated across the economic activities (Carlei and Nuccio, 2014; Carlei *et al.*, 2016).
2. A Euclidean distance is calculated to capture how similar the pattern allocation of local resources is across economic activities. In our case, the Euclidean distance measures the distance between the vector of (normalized) employment levels across two different sectors.³

¹ATECO 2007 is a hierarchical coding system adapted from the NACE- Statistical Classification of the Economic Activity in the European Union (Eurostat).

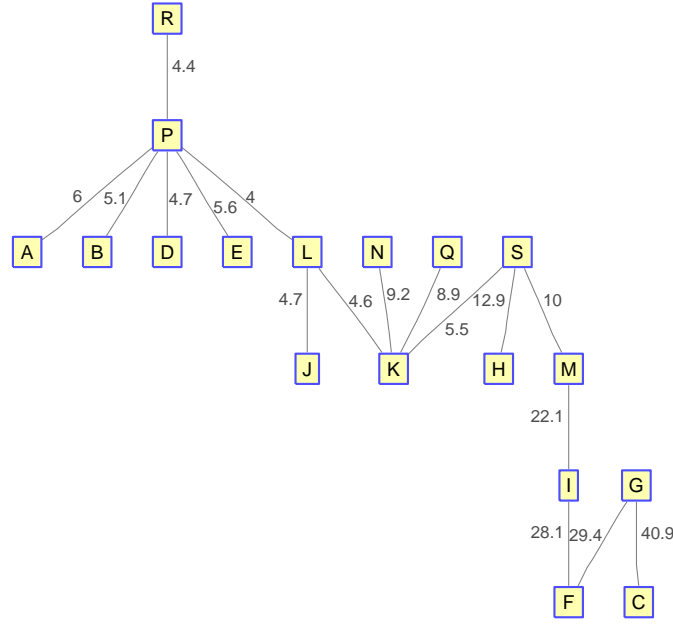
²Data are available in the census "IX Censimento Generale dell'Industria e dei Servizi" provided by the Italian statistical agency ISTAT (2011).

³Mantegna (1999) identifies, in his methodology, a metric which is defined using as a distance a function of the correlation coefficient computed between all pairs of nodes of the network.

3. The definition of the MST associated with the considered metric distance in order to define the indexed hierarchy between the n activities (nodes).

The application of our methodology to the database mentioned above allows us to map the Italian economic system in a topological space built on similarities of patterns in terms of industrial employment, as shown in the figure 1.

Figure 1: Spatial similarities across economic activities



Note: The chart represents the strength of the sectoral linkages in the network tree. Numbers on the vertices indicate Euclidean distance. Letters designate the 18 different sectors as follows: A: Agriculture, forestry and fishing; B: Mining and quarrying; C: Manufacturing; D: Electricity, gas, steam and air conditioning supply; E: Water supply sewerage, waste management and remediation activities; F: Construction; G: Wholesale and retail trade repair of motor vehicles and motorcycles; H: Transportation and storage; I: Accommodation and food service activities; J: Information and communication activities; K: Financial and insurance activities; L: Real estate activities; M: Professional, scientific and tech. activities; N: Administrative and support service activities; P: Education; Q: Human health and social work act.; R: Arts, entertainment and recreation; S: Other service activities.

Our methodology allows us to represent the Italian structure in terms of a network and to define, accordingly, the central activities (hubs). Indeed, as shown in figure 1, we obtain a graph with four hubs: (1) Real estate activities (L); (2) Finance and insurance activities (K); (3) Professional, scientific and technical activities (M), and (4) Education (P). We precise again that our methodology defines spatial similarities between activities by comparing local employment patterns. Table 1 highlights the linkages between couple of nodes and their similarity in terms of a Euclidean distance.

Irrespective of its size, an economic activity can be a hub when its employment patterns are identical across municipalities. For instance, *Education activities*

Table 1: Euclidean distance between nodes

Couple of neighboring nodes	Euclidean distance between nodes	Couple of neighboring nodes	Euclidean distance between nodes
(P, A)	6.2991	(L, J)	5.2079
(P, B)	4.9147	(L, K)	5.3741
(G, C)	23.9988	(N, K)	9.5026
(P, D)	4.6702	(Q, K)	8.7524
(P, E)	5.7809	(S, K)	6.2867
(G, F)	19.4226	(P, L)	4.5924
(I, F)	21.2333	(S, M)	11.2481
(M, H)	13.1660	(R, P)	4.6433
(M, I)	18.7914		

Note: The table documents the Euclidean distance between sectoral nodes. Colors represent the four different hubs: The real estate hub is represented in red, the professional services hub in green, the finance and insurance hub in blue and the education hub in purple; nodes without a color are not part of a hub network. Letters designate the 18 different sectors as follows: A: Agriculture, forestry and fishing; B: Mining and quarrying; C: Manufacturing; D: Electricity, gas, steam and air conditioning supply; E: Water supply sewerage, waste management and remediation activities; F: Construction; G: Wholesale and retail trade repair of motor vehicles and motorcycles; H: Transportation and storage; I: Accommodation and food service activities; J: Information and communication activities; K: Financial and insurance activities; L: Real estate activities; M: Professional, scientific and tech. activities; N: Administrative and support service activities; P: Education; Q: Human health and social work act.; R: Arts, entertainment and recreation; S: Other service activities.

constitute a hub, even though, on average, this sector only represents 0.46 per cent of total employment among our Italian municipalities (see table 4 in the appendix). Nevertheless, it is a hub because the employment rate is weakly identical across localities. Indeed, *Education activities* as a hub are connected with other activities with the same characteristics in terms of employment. We notice the connection among *Education activities* (0.46 per cent), *Arts entertainment and recreation activities* (0.96 per cent), *Water supply sewerage, waste management and remediation activities* (1.06 per cent), *Electricity, gas, steam and air conditions supply* (0.52 per cent), *Mining and quarrying activities* (0.20 per cent), *Agriculture, forestry and fishing activities* (0.39 per cent) and finally *Real estate activities* (1.71 per cent). The high connectivity of these activities stems from the low density of employment. *Real estate activities* – representing 1.71 per cent of total employment – are connected with *Financial and insurance activities*, *Information and communication activities*, *Accommodation and food service activities* as well as *Education activities*. *Professional, Scientific and Technical activities* represent a third hub with 7.22 per cent of employment.

The fourth and last hub is *Finance and insurance activities* – representing 3.64 per cent of total employment –, which are connected with *Administration and support services activities*, *Real estate activities*, *Other services activities*, *Human health and social work activities*. With four connections, this hub is the most connected one in our structure. This result is primordial regarding the propagation of an external shock. As indicated above, the objective of our analysis is to map an economic structure as a network in order to better analyse and understand the transmission of an exogenous shock. Taking into account the high level of connectivity of *Financial and insurance activities* and its important

economic role we have chosen to simulate the effect of a shock on this particular sector and analyse its transmission through the economic network structure.

5 Simulating an exogenous shock

In this section we will estimate and analyse the transmission of a shock spreading through the sectoral network. This way, we can observe how the presence of inter-linkages between economic activities could act as a propagation mechanism of shock through the economic system. In the framework of a network-based approach, we can argue that a shock hitting a highly connected economic activity (hub) could generate a cascading effect on the activities linked to it (Acemoglu *et al.*, 2012). In the previous section, we analysed the hierarchical structure stemming from similarities between urban employment patterns. Starting from a micro-economic approach, according to which the local employment morphology is a proxy of the local production system, we obtained a network that provides a representation of the economic structure at the aggregate level.

Based on this result, we simulate a shock hitting a node (economic activity) and analyse its transmission through the (economic) system. Let Y denote the total number of employees in each activity as our variable of interest. We assume that Y_i (total number of employees in node i -th) is influenced by the neighboring nodes, so we assume the existence of a linear relationship between the observation in the i -th node (Y_i) and its neighboring j -th nodes (Y_j), with $i \neq j$. We assume that this relationship is described by a first-order spatial auto-regressive model (FAR), as expressed in the following equation:

$$Y = \rho W \cdot Y + \varepsilon, \quad \varepsilon \sim N(0, \sigma^2 \cdot I_n) \quad (5)$$

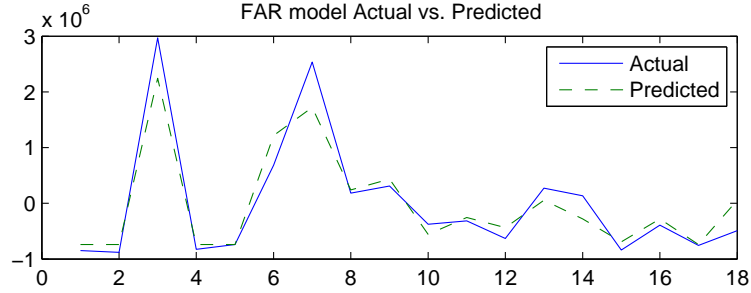
where Y is a $n \times 1$ vector whose elements represent the aggregate level of employment in each activity. The parameter, ρ , reflects the spatial dependence measuring the average influence of neighboring nodes on observations in the vector Y , with $\rho < 1$. The matrix W is an n -by- n spatial weight matrix. The elements of W are used to specify the spatial dependence structure among the nodes in the network: if node i is linked to node j , then $W_{i,j} > 0$. Otherwise, $W_{i,j} = 0$. The matrix is normalized to have row-sums of unity, in order to specify the vector $W \cdot Y$ as a linear combination of observations in related nodes; ε denotes the stochastic disturbance in equation (5) (see LeSage, 1999). Then the connectivity relationship that characterizes the spatial regression model allows us to evaluate how a variable changes in a given node (i -th) produces direct effects on the node from which it originated and indirect impacts on neighboring nodes. Finally, we assume a shock is introduced by the error term vector. Then, the change in Y arising from an exogenous stimulus originated from the i -th nodes could be expressed by the following expression, where $d\varepsilon$ is equal a $n \times 1$ vector, and its element are equal to zero except for the i -th equal to the amount of the shock:

$$\frac{dY}{d\varepsilon} = M(W) \quad (6)$$

In equation (6) the multiplier $M(W)$ takes the form of $(I - \rho \cdot W)^{-1}$, expressing the impact on the dependent variable that stems from an exogenous shock spreading through the network as a result of its impact on neighbouring nodes.

We applied the FAR model in order to shock the estimated Italian network as represented in figure 1. We will characterize this relationship in a two-steps procedure. Firstly, we estimate the spatial dependence. In order to achieve this result we will estimate the regression parameter ρ using as the first order contiguity matrix W the matrix of Euclidean distances between nodes. The dependent variable Y represents an n -by-1 vector of the observed total number of employees in each of the $n = 18$ economic activities, then Y will be a vector with as many elements as nodes (n). Also, Y is expressed in deviations from the means form in order to eliminate the constant term in the original model (LeSage, 1999). Regression results are shown in figure 2. As expected, the regression parameter ρ is estimated at around 0.9, indicating a positive spatial dependence where employment in an economic activity is positively related to a linear combination of those from related activities.

Figure 2: First-order spatial auto-regressive model estimates



Variable	Coefficient	Asymptotic t-Student	R^2	z-probability
ρ	0.886***	11.746	89.77	0.000

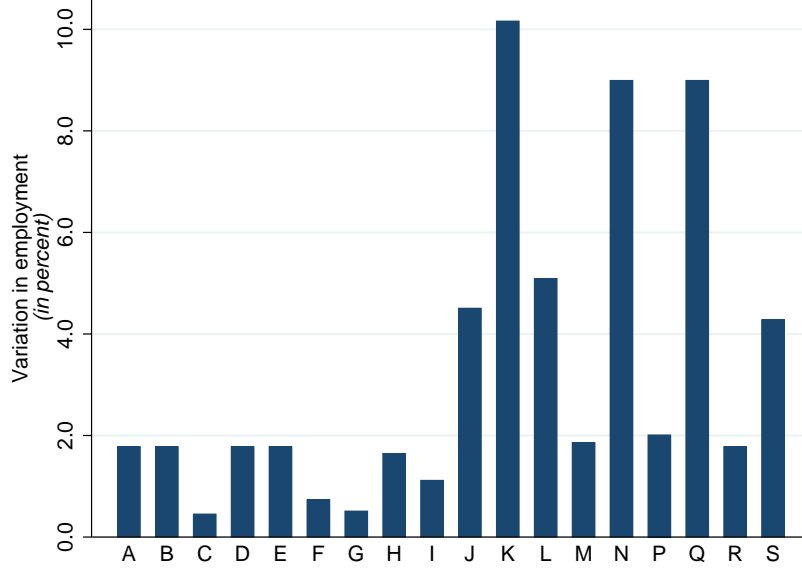
Once the spatial parameter has been estimated we will be able to introduce an external shock to the network. As mentioned above, in equation (6), $d\varepsilon$ is a vector of n elements that represents the magnitude of the shock. If we assume the shock originates only from the i -th node, then its elements are equal zero except the i -th that is equal to a fixed amount. Taking into consideration the economic role of the financial sector, we decided to concentrate on a shock to this specific sector in order to observe its reaction and the effect of a such a financial market shock on the rest of the economic structure. For that, it was primordial to define a value of the employment loss in the Italian financial sector following an external shock. We took the last financial crisis in 2008 as an example in order to define this value. Based on data from Eurostat we estimated that the financial sector in Italy lost around 10 per cent of employment between 2007 and 2014 (see table 2 below).

Table 2: Change in employment in Italy between 2007 and 2014 (in '000s)

Year	Financial activities	Education	Real estate, business and administrative ac- tivities
2007	666	1618	2530
2008	650	1576	2605
2009	639	1551	2373
2010	653	1508	2386
2011	651	1505	2359
2012	626	1452	2301
2013	616	1443	2360
2014	599	1482	2386
Employment loss 2007/2014	10%	8%	5.6%

Taking into account equation (6), we simulated an employment variation of about 10 per cent in the financial sector and estimated the multiplier effect (see below). Indeed we define the value of shock, $d\varepsilon$, equal to 3.7 per cent and we observe the effects of this shock hitting the financial sector in figure 3 and table 3. In light of the dependence structure, as we expected, the shock propagation produces significant effects on neighboring nodes and activities (notably sectors L, N, Q and S) more than 9 per cent while the effects are more muted in distant nodes (less than 2 per cent).

Figure 3: Change in employment following an exogenous shock of 3.7 per cent on *Financial and insurance activities*



Note: Letters designate the 18 different sectors as follows: A: Agriculture, forestry and fishing; B: Mining and quarrying; C: Manufacturing; D: Electricity, gas, steam and air conditioning supply; E: Water supply sewerage, waste management and remediation activities; F: Construction; G: Wholesale and retail trade repair of motor vehicles and motorcycles; H: Transportation and storage; I: Accommodation and food service activities; J: Information and communication activities; K: Financial and insurance activities; L: Real estate activities; M: Professional, scientific and tech. activities; N: Administrative and support service activities; P: Education; Q: Human health and social work act.; R: Arts, entertainment and recreation; S: Other service activities.

Moreover, we can examine the intensity of the effects on the sector where the exogenous stimulus originated. As shown in table 3, the value of the change on the employment level on the financial sector is about three times higher than the shock. This behavior can be explained intuitively on the basis of the autoregressive spatial models according to which a variation of a given node (region) is amplified by the presence of the multiplier that summarizes the combination of different effects linked to the topological structure of the system. LeSage and Fischer (2008) describe them as a direct effect, arising because the shock hitting the i -th node, and a second-round effect (indirect effect) that takes place due to a change in the level of employment in the i -th node passing through neighbours which in turn will affect the i -th node itself.

Table 3: Change in employment following an exogenous shock on financial and insurance activities

Economic activities (nodes)	Change in employment (in %)
A: Agriculture, forestry and fishing	1.83
B: Mining and quarrying	1.83
C: Manufacturing	0.47
D: Electricity, gas, steam and air conditioning supply	1.83
E: Water supply sewerage, waste management and remediation activities	1.83
F: Construction	0.76
G: Wholesale and retail trade, repair of motor vehicles and motorcycles	0.53
H: Transportation and storage	1.69
I: Accommodation and food service activities	1.15
J: Information and communication activities	4.59
K: Financial and insurance activities	10.26
L: Real estate activities	5.17
M: Professional scientific and technical activities	1.90
N: Administrative and support service activities	9.10
P: Education	2.07
Q: Human health and social work	9.10
R: Arts, entertainment and recreation	1.83
S: Other service activities	4.35

Note: The size of the shock amounts to 3.7 per cent of value added in financial and insurance activities.

Deepening the level of analysis, the network-based approach logic becomes even more compelling. In particular, we want to analyze the extent of the change in the number of employed persons depending on the position of each activity compared to the economic activity from which the shock originates. Let us call first-neighbours nodes those that are directly linked to the financial sector, second-neighbors nodes those that have a geodesic distance equal to two and far nodes those whose geodesic distance is more than three.

From this analysis it ensues that within these subgroups the level of connectivity affects the extent of shock propagation. Let us start by considering first-neighbours. Isolated nodes – such as ‘N: administrative and support service activities’ and ‘Q: human health and social work’ – absorb much of the shock effect. The variation in the number of employees due to a shock on financial activities is about 9 per cent. On the other hand, the external stimulus seems to only weakly hit the first neighbours linked to other nodes. In particular for ‘L: Real estate activities’, which are activities whose ties with the financial sector are easily explained, we found a weak effect when compared with isolated first neighbours (about 5.2 per cent), attributable to the fact that it is a node with links to two hubs (‘P: education’ and ‘K: financial and insurance activities’). Similarly, ‘S: other service activities’, plays the same role as it is connected with two hubs (‘K: financial and insurance activities’ and ‘M: professional scientific and technical activities’).

Indeed, focusing on the size of the estimated impact on second neighbours, such as ‘J: information and communication activities’ which is a second neighbour, at the same distance as ‘P: education’ and far away from financial activities and ‘M: professional scientific and technical activities’. The effect for the first one is higher (4.6 per cent) because of its position: it is an isolated hub in the middle of the network. Based on its position among the network its value of variation on the level of employment is higher because it could be referred to as an indirect effect of the shock that overtakes and turns back among the network. This effect is also amplified by lack of inter-linkages with other activities (isolated node). On the other end, nodes far away with respect to the origin of shock, such as ‘C: manufacture’, ‘F: construction’, and ‘G: wholesale and retail trade repair of motor vehicles and motorcycles’ and ‘I: accommodation and food service activities’, display only low variations in employment of less than 2 per cent.

The network-based approach is an original way in order to get important information regarding spatial inter-linkages among economic activities. Indeed, this approach allows us to highlight the centrality and the level of connectivity of each activity. This kind of information should prove primordial for policymakers as it is useful in order to better understand and analyse the transmission of an exogenous shock on any economic structure.

6 Conclusion

This paper has shown with an original methodology based on the network analysis that spatial linkages help us to define another dimension of sectoral dependency. Indeed, our analysis uncovers a hierarchical structure from the analysis of similarities between urban employment patterns. Starting from a micro-economic approach, considering the local employment morphology as a proxy of the local production system, we obtain a network that provides a representation of the economic structure at the aggregate level. This representation allows us to get a spatial interpretation of inter-linkages between different economic activities based on the connectivity and the centrality. Indeed, as we highlighted above, both characteristics help to indicate the level of resilience of each node in the case of an exogenous shock.

This information is helpful in order to better understand and analyse its effects. Indeed, a shock can cause economic fluctuations and structural adjustment processes across different industries, sectors or economic activities. Those that are less prepared, despite its high level of connectivity, or that are vulnerable to economic shocks suffer the most. This information allows to understand spatial dynamics and to define, consequently, their role in a regional policy.

Possible further extensions of our work include an application of our methodology to global supply chain systems in order to understand global economic dynamics from a network perspective, understanding connectivity and centrality of sectors and countries in the international division of labour. Other extensions of our methodology could also look into alternative sources of information such as input-output tables and combine them with information at the regional and local level where available, which would allow for a broader application of our methods in areas where information is sparse or not existent.

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7 Appendix: Distribution of sectoral employment

Table 4: Distribution of sectoral employment

Economic activities (nodes)	Employment level (average, in '000s)	Sectoral share (in per cent)
A: Agriculture, forestry and fishing	7.98	0.39
B: Mining and quarrying	4.10	0.20
C: Manufacturing	479.81	23.62
D: Electricity, gas, steam and air conditioning supply	10.53	0.52
E: Water supply sewerage, waste management and remediation activities	21.51	1.06
F: Construction	197.39	9.72
G: Wholesale and retail trade, repair of motor vehicles and motorcycles	426.44	20.99
H: Transportation and storage	135.45	6.67
I: Accommodation and food service activities	151.27	7.45
J: Information and communication activities	66.56	3.28
K: Financial and insurance activities	73.93	3.64
L: Real estate activities	34.82	1.71
M: Professional scientific and technical activities	146.64	7.22
N: Administrative and support service activities	129.78	6.39
P: Education	9.30	0.46
Q: Human health and social work	64.50	3.17
R: Arts, entertainment and recreation	19.44	0.96
S: Other service activities	52.22	2.57
Total	2031.67	100

Note: Figures show averages across the 8091 Italian municipalities.