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Abstract: This paper assesses the network robustness of the technological capability base of 269 European metropolitan areas against the potential elimination of some of their capabilities. By doing so it provides systematic evidence on how network robustness conditioned the economic resilience of these regions in the context of the 2008 economic crisis. The analysis concerns calls in the relevant literature for more in-depth analysis on the link between regional economic network structures and the resilience of regions to economic shocks. By adopting a network science approach that is novel to economic geographic inquiry, the objective is to stress-test the technological resilience of regions by utilizing information on the co-classification of CPC classes listed on European Patent Office patent documents. Findings from a regression analysis indicate that metropolitan regions with a more robust technological knowledge network structure exhibit higher levels of resilience with respect to changes in employment rates. This finding is robust to various random and targeted elimination strategies concerning the most frequently combined technological capabilities. Regions with high levels of employment in industry but with vulnerable technological capability base are particularly challenged by this aspect of regional economic resilience.

Keywords: regional economic resilience, network robustness, metropolitan regions, technology space

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1. Introduction

Regional economies across Europe show persistent disparities in economic performance and face a number of continuous structural challenges. Stagnating industrialised and peripheral regions suffer from a slow-burning decline in economic outcomes, while dynamic large urban agglomerations gain greater shares of high-wage jobs (*Iammarino et al. 2019*). In a broader context, the *OECD (2019)* reports that productivity in the least productive regions of an OECD country is on average 46% lower than productivity in its most productive one. In one-third of these countries, productivity growth is concentrated in a single region that already features a high productivity level, further increasing regional inequalities. Regions are also more exposed to external shocks due to their increasing openness and interdependencies with the global economy. European regions underwent a slow recovery in the aftermath of the global economic crisis of 2008. It took many regions more than 8 years to reach pre-crisis per capita GDP levels (*OECD 2019*). Recovery was also unbalanced across European regions amidst an overall downturn (*Dijkstra et al. 2015*), with some capital regions creating more than 50% of new jobs since 2006 in their respective country (*OECD 2019*), while other capital metro regions have been hit hard by the crisis. Finally, due to shifting industrial and occupational structures, as well as income polarisation, people in an increasing number of regions are experiencing their economic opportunities and welfare provision diminishing, which is directly linked to a growing political discontent (*Rodríguez-Posé 2018, Dijkstra et al. 2020*).

In response to these challenges, growing attention in academia and policy has been directed towards the notion of regional economic resilience. That is, the capacity of regional economies to withstand economic shocks and at the same time to retain their long-term ability to develop new growth paths (*Christopherson et al. 2010, Martin 2012, Boschma 2015, Webber et al. 2018, Martin & Sunley 2020*). Response and adjustment to multiple forms of disturbances affect regional development over time, particularly as major recessions tend to periodically disrupt economic growth and development in regions (*Simmie & Martin 2010, Martin 2012*). Differences in resilience across regions can even contribute to persistent uneven regional development (*Martin & Sunley 2020*), as resistance to and recovery from one shock is likely to influence the resilience of regions against subsequent crisis events (*Simmie & Martin 2010*). In short, the literature on regional resilience has recently been emphasising the ability of regions to adapt their industrial, technological, and institutional structures in an economic system that is constantly evolving. By stressing the long-term capacity to reconfigure the socio-economic structure (*Christopherson et al. 2010, Simmie & Martin 2010, Pike et al. 2010*), it is acknowledged that the need for economic renewal is ever present, although usually more stressing in times of crises (*Saviotti 1996*). Such capacity, however, is strongly conditioned by pre-existing regional resources and the historically formed economic structure (*Diodato & Weterings 2015, Webber et al. 2018, Xiao et al. 2018*).

However, despite considerable efforts, it is still unclear why some regions are more resilient than others (*Christopherson et al. 2010, Martin 2012, Martin & Sunley 2020*). In particular, we need a more detailed account on how the structure of the local economy leads to more or less resilient regions, as the economic structures of regions shape sensitivity to shocks, as well as recovery. This is because regions are collections of networked individuals, firms, industries, and institutions depending on one another (*Balland et al. 2015*). A region's economy can be depicted as a network in which nodes represent industries or technologies, while the links indicate the degree of relatedness between them (*Boschma 2015, Whittle & Kogler 2020*). Such networks inform us on how capabilities, emerging from a region's resources and sustaining its economic activities are combined (*Neffke et al. 2018*), conditioning the processes of developing new growth paths (*Neffke et al. 2011, Boschma et al. 2013*), as well as sensitivity to shocks (*Balland et al. 2015*). Nevertheless, further evidence disentangling the sensitivity of these networks to various economic crisis events is still needed. The ongoing corona virus pandemic is the most recent manifestation of these fractured networks as both global and local value chains around the world have been severely shocked (*Gereffi 2020*). In fact, *Boschma (2015, pp. 714)* noted that "*in the regional resilience literature, it is remarkable how little attention has been paid to the sensitivity of regional networks to the removal of specific nodes or the dissolution of particular linkages.*"

This is precisely the issue the present investigation aims to tackle, *i.e.* to assess the robustness of a region's network structure against the elimination of some of its nodes (technological capabilities), and to provide systematic evidence on how this network robustness conditions the economic resilience of regions. To do so, we employ patent data from the European Patent Office (EPO) worldwide PATSTAT statistical database, and construct a network of the technological capabilities of 269 metropolitan regions across Europe. In these networks, nodes represent one of 654 technology classes appearing on patents associated with a region based on inventor location, while links demonstrate the frequency with which these technologies are combined (co-occur on a specific patent document). Inventions codified in patents can be viewed as distinct technological capabilities combined to achieve a specific outcome (*Strumsky et al. 2012*). In this spirit, the network of technologies combined within regions represents an instantiation of the local capability base deployed to reach economic outcomes such as employment, income, and innovation (*Kogler et al. 2013, Rocchetta & Mina 2019, Whittle 2020*). Next, drawing from the network robustness literature (*e.g., Albert et al. 2000, Solé et al. 2008, Barabási 2016, Zitnik et al. 2019*), we stress-test these technology networks by sequentially eliminating nodes until they are severely fragmented, representing shocks affecting the local technological capability base. In this way we obtain a measure of network robustness for each European metropolitan region. These measures are then validated by means of regression analysis for the case of the Global Economic Crisis of 2008, where we link the regional economic resilience in terms of change in employment rate to the robustness of the local technological capability network. The required socio-economic indicators are derived from the European Regional Database (ERD) provided by *Cambridge Econometrics*.

This paper contributes to the literature on regional economic resilience by revealing the link between resilience and the technology network structure of regions and by adopting a measurement approach from network science that is novel to economic geography. Combining the state-of-the-art in regional resilience and network robustness research, it answers the call for a more detailed understanding on the role that networks play for resilience (*Boschma, 2015*). This is conceptually consistent with the accepted interpretation of regional resilience in an adaptive capacity framework that is reflected in the structure of the local capability base.

In short, our findings indicate that metropolitan regions with a more robust technology network structure exhibited higher levels of resilience with respect to changes in their industrial employment rate during the economic crisis of 2008. This finding is robust to various random and targeted elimination strategies concerning the most frequently combined technological capabilities, and even after controlling for established regional economic structure measures such as related and unrelated variety (see *Quatraro 2010, Rocchetta & Mina 2019)*. Traditional industrial regions are particularly challenged by this aspect of regional economic resilience.

The following section offers a brief overview concerning the empirical literature on regional resilience. *Section 3* provides details on the datasets utilized in the present investigation, the proposed novel measure of regional resilience, and the econometric model specification. Results are described in *Section 4*, while the final section contains a detailed discussion of the findings and further considerations.

2. Regional economic resilience and network robustness

Despite a rapidly growing corpus of literature on regional resilience (see most recently the *Handbook on Regional Economic Resilience*, *Bristow & Healy 2020a*), a coherent body of theory behind the concept is still developing (*Martin & Sunley 2020*). Current perspectives have drawn on an interdisciplinary pool of ideas (*Pendall et al. 2010*), converging on two main approaches. The first, driven by equilibrium analysis in economics, is concerned with whether and how rapidly a regional economy returns to its normal (pre-shock) state in terms of aggregate economic outcomes, such as employment or income. Thus, regional resilience is interpreted as an ability to "bounce back" after a shock. A related approach, having its roots in ecology, suggests that those regions that exhibit higher levels of resilience are better able to absorb more severe shocks before shifting to a new equilibrium state (*Pendall et al. 2010, Martin 2012*). In this sense, one may consider resilience to entail the ability of regions to absorb shocks while retaining their core economic structure and level of economic performance. However, such accounts are incomplete in the sense that the capacity of regions to maintain economic success over the long-run rests not only on a return to normality after an economic shock, but on the adaptive ability of regions to reconfigure their economic structure in the face of such shocks (*Simmie & Martin 2010, Martin 2012, Boschma 2015, Bristow & Healy 2020b*).

Following this critique, the literature in recent years has moved away from the equilibrium-based approach in favour of a more evolutionary theory on regional resilience. This approach, drawing on evolutionary economics and evolutionary economic geography, emphasises the interacting elements of a local economy, producing more or less adaptable systems (*Pendall et al. 2010, Martin 2012, Kogler 2015*). Moreover, regions are viewed more in the context of their own history (*Boschma 2015, Webber et al. 2018*), as the set of previous economic activities conditions which economic structures are feasible for a given region and which are not (*e.g., Neffke et al. 2011, Boschma et al. 2013, Boschma et al. 2015, Rigby 2015*). Hence, a distinctive feature of an evolutionary approach to regional resilience is that it considers both the short-term ability to respond to shocks and the long-term ability of regions to develop new growth paths (*Pike et al. 2010*, *Boschma 2015, Martin & Sunley 2020*). From this evolutionary perspective a resilient region is able to change its economic structure in anticipation or in response to an economic shock.

The concept of resilience holds ample theoretical complexity with four interrelated dimensions, as proposed by *Martin (2012)*. *Resistance* refers to a region's sensitivity to shocks, while *recovery* means the speed and extent of climbing out of such a disruptive event. *Re-orientation* refers to the extent to which the region undergoes a structural change in response to the crisis event, and the implications for economic outcomes, such as employment, output, and income. Finally, *renewal* captures the extent to which a region resumes its pre-shock growth path. With respect to shocks, the majority of studies on regional resilience focus on sudden crisis events, such as natural disasters and the global financial crisis of 2008 at the global scale (*e.g., Xiao et al. 2018, Doran & Fingleton 2018, Cainelli et al 2019*), or major plant closures at the local scale (*e.g., Eriksson et al. 2018*). Defining regional resilience in the context of new growth paths relates to the distinction between changes within a preconceived path, referred to as *adaptation*, and the ability to develop new growth paths, referred to as *adaptability* (*Christopherson et al. 2010, Pike et al. 2010*). It is unclear, however, how regions may overcome the tension between exploiting their existing knowledge base without sacrificing adaptability (*Boschma 2015*).

While regional resilience is defined as a multi-dimensional concept it is understood mainly in relation to a system's structure, performance, and overall functioning (*Bristow & Healy 2020b*). Performance here refers to an acceptable growth path in terms of employment, output, income and innovation (*Martin 2012, Balland et al. 2015, Cappelli et al. 2020*). Persistent spatial disparities then lead to the question of why resilience varies from region to region, and what are the determinants of such adaptive capacity. Broadly speaking, the determinants being explored in the regional resilience literature are industrial and business structure, labour market conditions, financial arrangements, governance arrangements, and agency and decision-making aspects (*Martin & Sunley 2020*). In this paper, we contribute to the understanding of regional resilience by applying network science tools to further explore the first of these determinants.

A region's industrial structure is a central determinant of regional resilience both in terms of resistance and recovery. As a form of portfolio-effect boosting resistance, a diverse industrial structure may spread the risk of output demand and input supply fluctuations, and exposure to industry-specific external and internal disturbances (*Doran & Fingleton 2018*). For instance, EU regions with a large share of medium and high-tech industries were found to be more resilient in terms of resistance during the 2008 crisis. In terms of recovery, a diverse composition of industries may offer more market opportunities and chances for recombining existing regional capabilities in new ways (*Martin & Sunley 2020*). This means that a diverse economic structure will likely score high on adaptability as it would provide a number of potential growth paths to fall back on (*Boschma 2015*). From this point of view, specialisation into a few core activities makes a region more vulnerable against economic shocks, except perhaps when specialising in the leading industries of the current wave of technological change (*Brakman et al. 2015*). However, such novel industries, relying on complex knowledge, tend to cluster in large cities (*Balland et al. 2020*), making this a less viable option for peripheral places.

Advancements in evolutionary economic geography indicate that considerations on the local economic structure should go beyond the diversity-specialisation dichotomy (*Kogler 2015, Whittle & Kogler 2020*). In particular, it has been shown that the related variety of economic activities contributes to regional growth, most prominently in terms of employment (*Frenken et al. 2007*). Related variety here means those industries that are not too similar, nor too different in terms of productive knowledge, fostering desirable levels of cognitive proximity and interactive learning (*Boschma 2005*). Nevertheless, there is a tension here. On the one hand, more local industries related by similar competencies or input-output linkages are beneficial for the long-term economic success of a region. This is because related variety offers opportunities for growth, as well as diversification through the entry of related economic activities (*Kogler et al. 2017*). On the other hand, an economic crisis may also propagate itself easier through a local economy characterized by many related components (*Martin & Sunley 2020*). Still, it is unclear how related variety within the local economy shapes regional resilience (*Boschma 2015, Martin & Sunley 2020*).

Yet, to understand the economic structure as a determinant of regional resilience, we need to consider this structure more explicitly. Networks are of assistance here as regional economies can be regarded as webs of specialized production units, largely dependent on the technologies, skills and tacit knowledge integrated in the process of value creation (*Boschma & Martin 2010*). Indeed, economies of regions have been characterized as knowledge networks, where nodes represent industries or technologies, while links represent the level of technological relatedness between them (*e.g. Neffke et al. 2011, Kogler et al. 2013, Boschma 2015, Whittle 2020*). As such, these networks allow us to infer how capabilities are being combined and shared among economic activities of a region, translating to different levels of economic outcomes. These local capabilities emerge from a region's resources and sustain its economic activities (*Neffke et al. 2018*). Knowledge and skills available locally are prominent sources of localized capabilities, contributing to the lasting competitive advantage of regions (*Maskell & Malmberg 1999*). For technological knowledge in particular (*e.g., Kogler et al. 2013, 2017, Boschma et al. 2015, Lee et al. 2019*), such networks map how particular technological capabilities are being combined to achieve economic outcomes (*Strumsky et al. 2012*). One can expect then that the level of disruption by an economic shock would depend on the region-specific structure of the technological capability base.

Indeed, empirical evidence indicates that regions of the UK with higher average relatedness of technologies have suffered less in terms of employment growth from the Great Recession of 2008 (*Rocchetta & Mina 2019*). US metropolitan areas with more options for diversification into technologies that are related to their current portfolio were found to be less likely to be severely affected by a crisis (*Balland et al. 2015*). Finally, evidence indicates that those EU regions that are able to maintain knowledge production in the face of adverse shocks tend to be more resilient in terms of unemployment as well (*Cappelli et al. 2020*). However, to move forward, there is a need to connect specific aspects of the technology network structure of a region with more or less resilience in terms of economic outcomes. In this paper, we put forward that network science offers crucial insights on this.

Complex adaptive systems (CAS) represent a promising interface between the evolutionary conceptualisation of regional resilience and network science. Broadly speaking, CAS research is an interdisciplinary approach aimed at understanding how interactions and self-organisation at the micro-level is linked to the functioning and behaviour of a system at the macro-level. What matters for us here is that complex systems have the potential to adapt their structure and dynamics in response to external or internal changes in the environment (*Martin & Sunley 2007*). The interpretation of regional resilience as adaptability resonates with that of robustness in CAS research, referring to the ability of a system to retain its functionality through structural change in the face of internal or external disturbances (*Kitano 2004*). For instance, the functionality of a region can be interpreted as the level of employment, output or income (*Martin 2012*). Finally, studying the structure and dynamics of CAS in general and regional economies as complex systems in particular, relies heavily on a network conceptualization of regions (*e.g. Boschma 2015*). For this reason, *Martin & Sunley (2007)* argue that a network perspective needs to be further developed in economic geography.

In the context of network science, the robustness of a network refers to the ability to carry out its basic function even when some nodes or links are missing (*e.g. Albert et al. 2000, Solé et al. 2008, Barabási 2016, Zitnik et al. 2019*). In a structural sense, for regions this would mean a desirable level of economic outcome is maintained, even after some industries, technologies or their connections disappear, *i.e.* suffer a major crisis event. To these ends, *Boschma (2015)* has explicitly called for future studies to focus on the robustness of regional economic networks against the elimination of nodes, or the dissolution of links.

The general argument here is that the underlying network structure conditions the robustness of complex systems, *i.e.* the ability to withstand random failures and targeted attacks. Here, two key insights are to be taken from network science that also resonate with our understanding of the nature of economic crises in regions. First, a complex system fails to carry out its basic function (desirable economic outcomes in our case) when the underlying network is fragmented into too many disconnected components (*Barabási 2016*). Crucially, such fragmentation tends to happen suddenly, rather than gradually (*Cohen & Havlin 2009*). That is, up to a threshold, removing nodes from a network leaves the connected part of the network containing a large proportion of nodes (*i.e.* the giant component) relatively intact. However, when the extent of node failures passes this threshold, the network falls apart. The threshold here signifies a phase transition from a giant component of industries well connected to others or technological capabilities frequently combined with one another, to many small and disconnected clusters of economic activities, severely disrupting the interdependencies within the local economy, and thus hindering economic performance.

Second, the robustness of a network structure depends on the kind of way the nodes are eliminated (*Albert & Barabási 2002*). Networks with a more skewed distribution of connections across nodes, *i.e.* few nodes having many connections, while many nodes having just a few, tend to be highly robust against random disturbances. This is because these networks involve only a small number of critical nodes with respect to their cohesion. However, such networks are highly susceptible to the failures of these hubs. In our case, this would mean that specialised regions would fare well against a shock affecting a random activity, but would be very vulnerable if one of their core activities were impacted. Finally, the economic resilience of the local industry and technology networks would be the number of failures they could withstand before the network becomes fragmented into too many disconnected components (*Molloy & Reed 1995*), dissolving the technological capability base of the local economy.

This paper will test this expectation in the context of European metropolitan regions' technological capability bases for the test-case of the 2008 economic crisis. Amidst overall downturn, cities across Europe proved to be key in resistance to and recovery from the global financial crisis, with some capital regions being responsible for creating more than 50% of new jobs since 2006 in their respective country (*OECD 2019*). However, other capital metro regions have been hit hard, and recovery overall was highly uneven across European regions (*Dijkstra et al. 2015*). All in all, recovery in the aftermath of the global economic crisis was slow, as it took many regions more than eight years to reach pre-crisis levels of per capita GDP (*OECD 2019*). Key insights into this variation in regional resilience show that pure urban size was not sufficient for resilience: among others, the quality of economic activities and production factors hosted were crucial in this context (*Capello et al. 2015*). Furthermore, EU regions with a higher share of population in commuting areas (but not in cities *per se*), and with a large share of medium and high-tech industries were found to be more resilient in the short-run (*Brakman et al. 2015*). Findings on US metropolitan areas and UK regions also stress the importance of technological structure in limiting the severity of crisis events (*Balland et al. 2015, Rocchetta & Mina 2019*). By focusing on European metropolitan areas, we provide novel evidence cutting across national borders on the structural determinant of regional resilience leading to the varied impact of the 2008 crisis in Europe.

3. Data and Methods

3.1. Data

For our investigation we rely on two different data sources. Firstly, patent data from the European Patent Office (EPO) *PATSTAT* database that covers all European NUTS3 regions. Throughout economic geography, patents have become a crucial data source on the structure and evolution of technological capability bases within regions (*Kogler et al. 2013, 2017, Boschma et al. 2015, Rigby 2015, Balland & Rigby 2017, Balland et al. 2019*). All patents have been assigned to at least one, but most of the time, multiple classification terms (CPC) indicating the technological knowledge domain to which the patent is connected. As such, patents inform us on which technological capabilities were combined to achieve a specific outcome (*Strumsky et al. 2012*). CPC codes are following a strict structure and may be available on the most detailed 8-digit level.

Secondly, we make use of the *Cambridge Econometrics*' European Regional Database (ERD) as a source of economic measures covering the period of 2006-2012. ERD contains a wide range of demographic and economic data for EU 28 countries at the regional level. We use employment data to construct the main dependent variable, which covers all individuals engaged in labour market activity. In the estimations, we include the volume of gross value added (GVA), which is the net result of outputs deflated to 2005 prices in Euro. The population of a region is used to control for potential scaling and agglomeration effects.

As one labour market could be a combination of multiple administrative units, we identify metropolitan areas using the Urban Audit's Functional Urban Area of at least 250 000 inhabitants, as identified by EUROSTAT[1]. According to this definition, each Metropolitan Area consists of at least one NUTS3 region, and also includes adjacent NUTS3 regions if more than 50% of the population belongs the commuter belt around the city. This approach adjusts for the bias caused by commuting, as without this correction, the comparison of the economic indicators would be far more complicated, since the borders of the NUTS3 regions reflect artificial constraints.

3.2. Variables

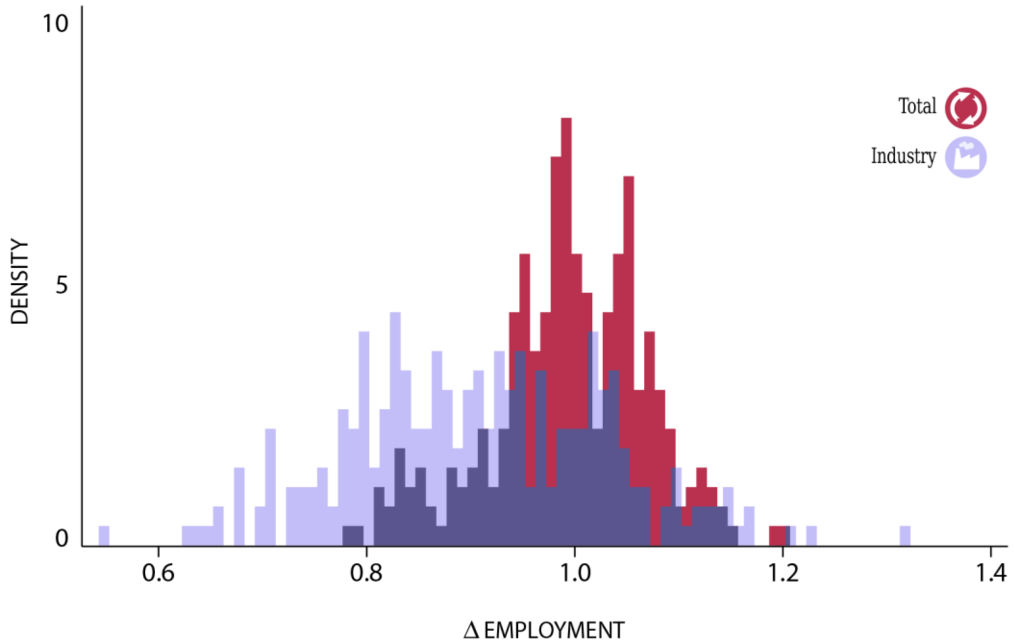
Regional economic resilience is frequently measured by employment (*Fingleton et al. 2012*, *Han & Goetz 2015, Rocchetta & Mina 2019*). *Martin* (*2012*) shows that using employment change as a dependent variable is a suitable empirical strategy to evaluate exogenous economic shocks. While the shift of employment clearly reflects a capacity of the region to adapt to exogenous shocks, it is a measure of resilience as an outcome rather than a source. *Boschma (2015)* points out that a distinction is needed between cause and effect of regional resilience: structures, networks and institutions are main determinants of regional resilience, while a desirable level of economic outcome is an indication of resilience. Hence, a resilient structure makes a resilient region. Therefore, in the empirical analysis, we link changes in employment to the underlying robustness of the technological capability base. We define our dependent variable as the following:

$$\Delta Emp_i = \left(\frac{Emp_{i,2012}}{Pop_{i,2012}}\right) \Big/ \left(\frac{Emp_{i,2006}}{Pop_{i,2006}}\right) \tag{1}$$

As the propensity for patenting differs across industries, the technological capability base of a region is likely most relevant for local industries with more patenting, such as in manufacturing (*EPO & EUIPO 2019*). We account for this by comparing model estimates using employment change for all sectors and for the *industry sector* in particular (B-E sections of NACE Rev. 2). The latter version of the dependent variable indicates wider dispersion during the 2008 crisis (*Figure 1*).

[1] https://ec.europa.eu/eurostat/web/metropolitan-regions/background

Figure 1. The distribution of the dependent variable by employment categories.



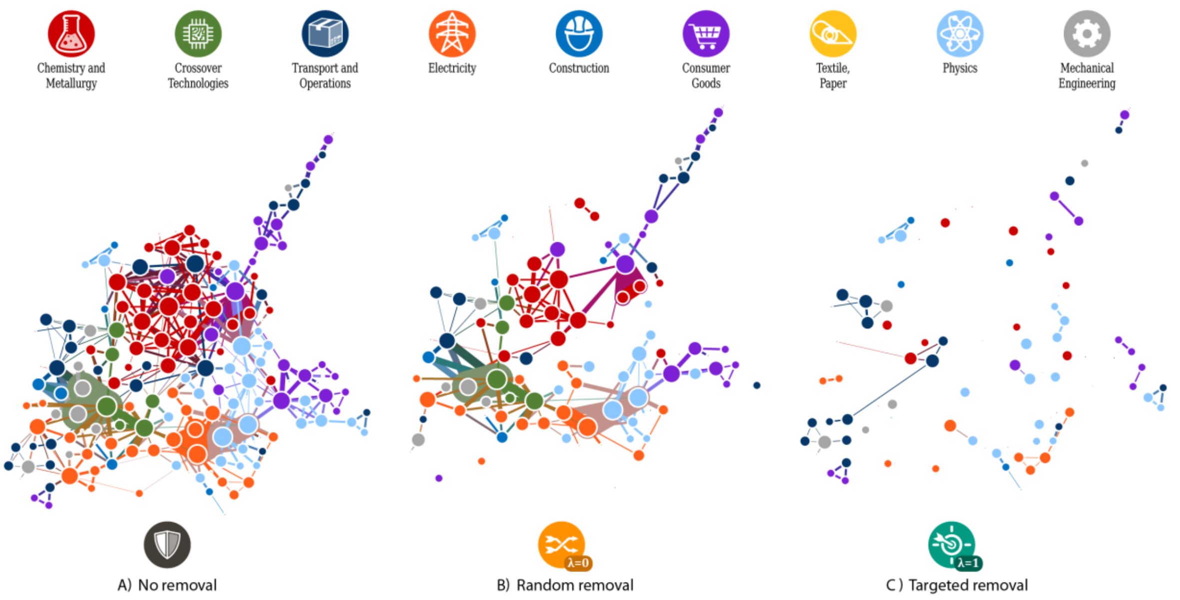
To construct our measure of technology network robustness, we first constructed technology networks for each European metropolitan area. In these networks, each node represents a technological capability (one of 654 CPC classes), while the weight of links are proportional to the number of patents that combine the pair of technologies, thus representing the frequency with which the two capabilities are combined in a region. Next, we simulate exogenous shocks by gradually removing nodes from these networks. It is widely documented that natural, social and economic systems are sensitive to such cascades (*Wang et al. 2009, Barabási 2016, Karsai et al. 2016, Zitnik et al. 2019, Lengyel et al. 2020*).

Let Ω denote the amount of node removal that a region's technology network could withstand without being fragmented into many unconnected components. Formally we identify this threshold of connectedness by the Molloy-Reed criterion for having a giant component (*i.e.* a part of the network that contains essentially all nodes or links) (*Molloy & Reed 1995*): $\langle k^2 \rangle / \langle k \rangle > 2$, where $\langle k^2 \rangle$ is the average squared number of links of nodes and $\langle k \rangle$ is the average number of links each node has. Accordingly, Ω ranges on $[\varepsilon, 1)$, where ε represents the smallest possible value that is greater than zero, while the measure never goes up to 1, as no such system could exist that would survive the elimination of all of its nodes. In essence, Ω shows the critical threshold of removing technological capabilities up to which the structure of a region's capability base likely enables the normal functioning of its economy. Our expectation is that regions with a high Ω would be better able to withstand an economic shock than regions with a low Ω.

We introduce the parameter λ to capture the empirical observation that some network structures are more robust to the random elimination of nodes, while others are more robust to the elimination of well-connected nodes (*Barabási 2016*). This parameter ranges on $[0,1]$ and operationalises the amount to which the degree-distribution is considered in the removing process. λ equals to 1 if the removing algorithm is targeting the technological capabilities with the highest level of degree centrality, which could be considered a worst-case scenario of an economic shock. When $\lambda = 0$, the algorithm follows a randomized removing process. Random failure is a frequently observed phenomenon in natural networks (*Barabási 2016, Zitnik et al. 2019*), and its mathematical properties let us simulate a proportional shrinkage of the technological capability base of regions. In between, $\lambda = 0.5$ for instance, would imply a removing process considering the same weight for nodes with high degree centrality and randomly selected nodes. Let Ω^{λ} denote the network robustness of a region's technology network structure. $\Omega^{\lambda=1}$ and $\Omega^{\lambda=0}$ together defines the two boundaries of network robustness against an economic shock. That is, a region's technology network is robust to random failures if it is able to withstand a large number of random eliminations (high $\Omega^{\lambda=0}$), and it is robust to disturbances to its most frequently combined technological capabilities if it is able to withstand a large number of targeted eliminations (high $\Omega^{\lambda=1}$). Note that the aim here is not to simulate a shock-propagation pattern but rather to measure the extent of being able to resist a certain type of capability-elimination.

Figure 2 illustrates the measurement approach to network robustness for the case of Dublin's technological space. *Subfigure 2A* shows the full network without any shocks. The colour of a node represents the broad economic sector that primarily utilizes that specific technology class, while the node size corresponds to the number of patents belonging to the technology class. The weight of the link between two nodes is proportional to the co-occurrence of the two technology classes on patents. *Subfigure 2B* Shows 40% of nodes removed from the network randomly. When we remove the nodes randomly from the network, the amplitude of the average-degree decreases proportionally to the number of nodes removed. Therefore, random failures correspond to a linear effect of economic crises. In *Subfigure 2C* 40% of the nodes are removed based on their degree centrality. We can observe that with 40% of random attacks the giant component still exists and technologies still connect to each other, while the same amount of a targeted attacks fragment the network into unconnected to components (see more detailed illustrations in *Supplementary Figure 1* and *2*).

Figure 2. Random and targeted elimination of technological capabilities from Dublin's technology space (40% of node removal).



In the econometric estimation we control for a number of structural variables that may also contribute to the resilience of regions. First, we include related and unrelated variety, identified as key structural characteristics with respect to resilience (*Xiao et al. 2018, Rocchetta & Mina 2019*). Following *Frenken (2007), unrelated variety* (UV) captures the variety of technology codes between higher-order groups (1-digit level), and *related variety* (RV) captures the degree of variety within the group (3-digit level)[2]. Unrelated variety or in other words between-group entropy is given by:

$$UV = \sum_{i \in S_j}^{J} P_j \log_2 \left(\frac{1}{P_j} \right) \tag{2}$$

[2] For an overview of the CPC classification scheme, see https://www.cooperativepatentclassification.org/cpcSchemeAndDefinitions/table

where $P_j = \sum_{i \in S_j} p_i$ is the probability of a given patent falling into a technological category S_j. *Related variety* is given by summing the within-group entropy of each technological class:

$$RV = \sum_{j=1}^{J} P_j \sum_{i \in S_j} \frac{p_i}{P_j} \log_2 \left(\frac{1}{\frac{p_i}{p_j}} \right) \tag{3}$$

hence RV quantifies the average degree of variety of 3-digit CPC classes of patents within a 1-digit main section.

Second, we control for *average clustering*, which is the probability that two neighbours of a randomly selected node link to each other (*Barabási 2016*). In the context of regions' technological capability base, a higher level of average clustering would indicate a more tightly-knit core of frequently combined technologies. Formally, the clustering coefficient shows the degree to which the neighbours of a given node connected to each other:

$$C_j = \frac{2L}{k_j(k_j - 1)} \tag{4}$$

where L is the number of links between k_j neighbours of node j. $C_j = 0$ if there is no connection between the neighbours of technology j, while it gives a value of 1 when all the neighbours of j are connected. C_j implies that there is a 50% chance that two neighbouring technologies of j are also connected to each other. Average clustering coefficient captures the degree of clustering of the full network. Mathematically the average clustering coefficient is defined by taking the average values of node-level clustering values, $\langle C \rangle = \frac{1}{N} \sum_{j=1}^{N} C_j$.

However, the concept of clustering is sensitive to the size of the network (*Barabási 2016*). Bigger networks tend to have a smaller clustering coefficient as the probability of closed triangles drastically decreases by increasing the size of the network. Hence, we cannot effectively compare the clustering coefficient of networks with a different number of nodes. Therefore, as null-models for each region to normalize the observed average clustering coefficient, we construct Erdős-Rényi random graphs, *i.e.* networks with the same number of nodes and average number of links for each node as the observed network. Our final variable can be expressed as:

$$C' = \frac{\langle C \rangle}{C_{ER}} \quad (5)$$

where C_{ER} refers to the clustering coefficient of the corresponding Erdős-Rényi random network.

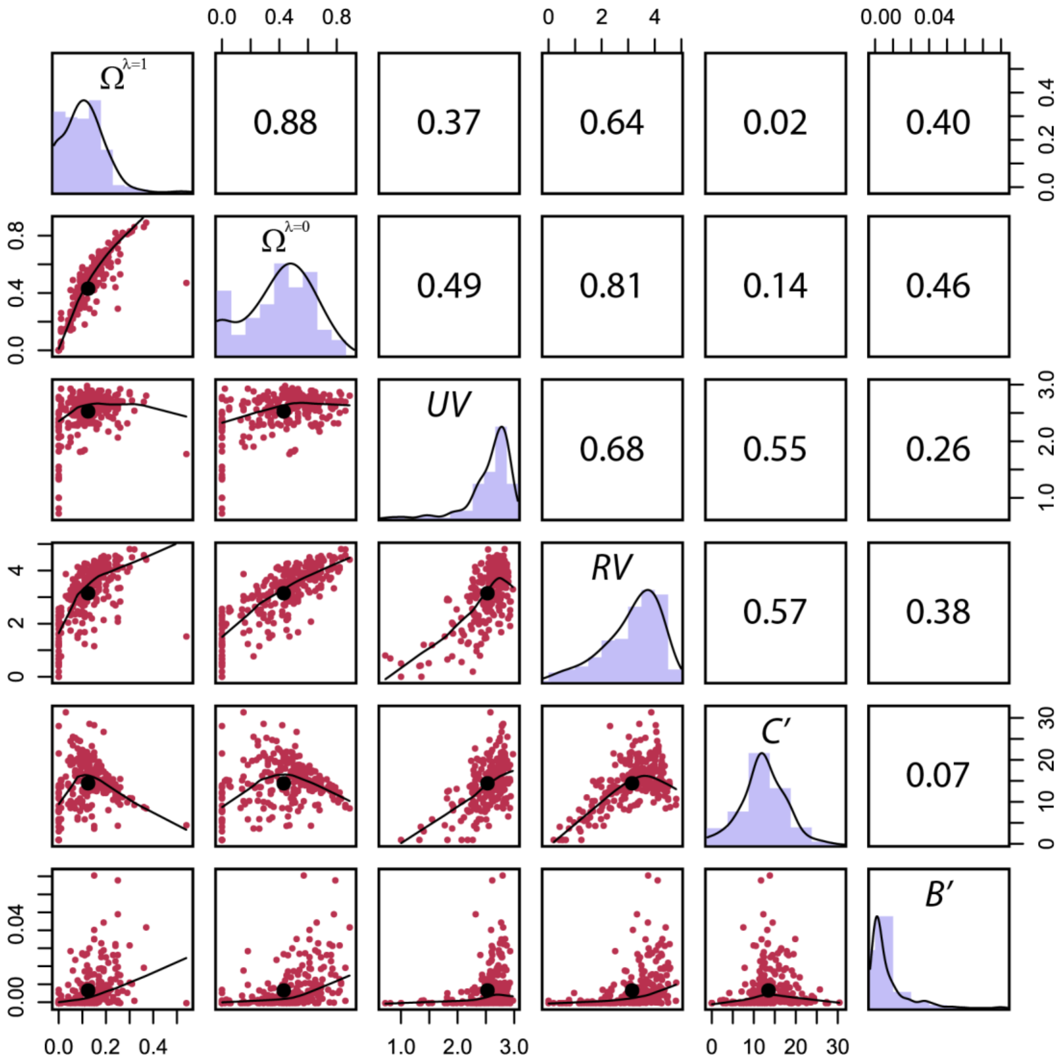
Finally, following *Balland et al. (2015)*, *bridging* is measured as the normalized betweenness centrality score for each region based on their position in inter-regional collaboration network. The collaboration network comes from the co-inventor collaborations that connect European metropolitan areas to one another. The strength of the connection between two regions is proportional to the weighted number of patents that list at least one inventor in each region. Betweenness captures how critical the region is as a bridge between randomly selected other regions, accessing knowledge flows from other metropolitan areas, which may compensate for disturbances to the technological capability base, hence contributing to resilience.

The univariate and bivariate distributions of our key variables, as well as the correlation coefficients are reported in *Figure 3*, indicating a high correlation between the network robustness measures and related variety in particular. Additionally, the two extreme λ lambda parametrizations of network robustness correlate substantially, however they enter models separately. Further examination of model VIF values indicated that multicollinearity should not be an issue in the econometric models.

3.3. Econometric Models

To analyse the connection between regional resilience in terms of employment change and technology network robustness, we apply a linear regression model. While the unit of observation follows the EUROSTAT classification of the European metropolitan areas, we cannot treat the observations as an independent random sample of cities across Europe. Hence, the employment residual is likely to be correlated within national borders. Moreover, regional resilience is linked to being embedded in the national institutional context (*Webber et al. 2018*). To overcome this potential bias, we use clustered standard errors on the country level.

Figure 3. Distribution and correlation matrix of explanatory variables.



Our model specification to disentangle the effect of technological structure on employment change is the following:

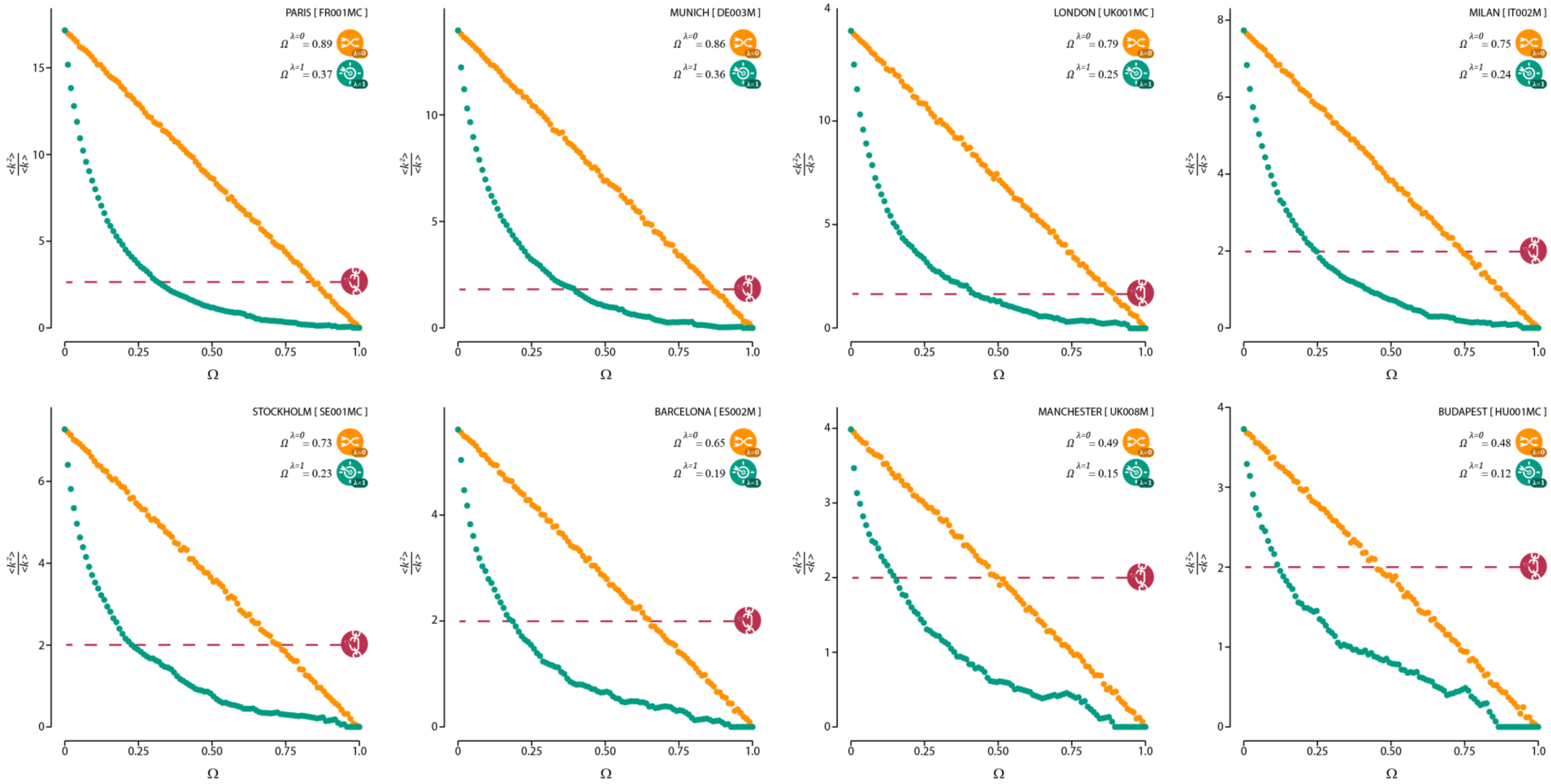
$$\frac{Emp_{i,t+1}}{Emp_{i,t}} = \alpha + \gamma_1 \Omega_i^{\lambda} + \beta_1 [\mathbb{Z}_{i,t}] + \beta_2 [A_{i,t}] + e_{i,t} \tag{6}$$

Where $\frac{Emp_{i,t+1}}{Emp_{i,t}}$ captures the regional resilience as outcome based on the change in employment from 2006 to 2012. $\mathbb{Z}_{i,t}$ is a collection of control variables that describes structural aspects of the technological capability base of a region: related- (*RV*) and unrelated-variety (*UV*), connectedness (*C′*), and bridging position (*B′*). $A_{i,t}$ stands for a vector of socio-economic control variables: the base level of employment $\log(Emp_{i,t})$, economic development level $\log(GVA_{i,t})$, and the population of the region $\log(Pop_{i,t})$. $e_{i,t}$ refers to the normally distributed error term of the base year 2006. We denote network robustness by Ω_i^λ where λ captures the degree to which the connectedness of nodes is considered during node-elimination.

4. Results

First, we present exploratory results on the robustness of technological capability networks for a selection of eight European metropolitan areas to illustrate our measurement approach (*Figure 4*). The first noticeable feature of these metropolitan technology networks is that they are robust to random failures ($\lambda = 0$) but much more fragile to the targeted removal of their most well-connected technologies ($\lambda = 1$). That is, the technology structures of these regions do not fragment to many disconnected components even after a series of technological capabilities disappear at random. Such capacity could be interpreted for instance as a robustness against the obsolescence of a given technology class. However, the same regions are very much vulnerable to disturbances of a similar magnitude to the capabilities that are most frequently combined within the region. This reflects that regions tend to have a discernible knowledge profile with some core capabilities (*Kogler et al. 2013, Rigby 2015, Boschma et al. 2015*). For instance, for the technology space of Paris to reach its threshold for becoming fragmented into many disconnected components, almost 90% of its technological capabilities need to be removed, while the same network reaches this threshold after removing only 37% of its most connected (most frequently combined) technological capabilities. This dual characteristic is in fact also found in collaboration, communication and infrastructure networks including scientific collaborations, mobile phone calls and the world wide web (*Barabási 2016*). Second, we observe a considerable variation of technology network robustness across metropolitan areas as Munich for instance can withstand the removal of 36% of its most well-connected technologies before the fragmentation of its technology network, while Manchester's technology structure can tolerate the removal of only 15% of its frequently combined technologies.

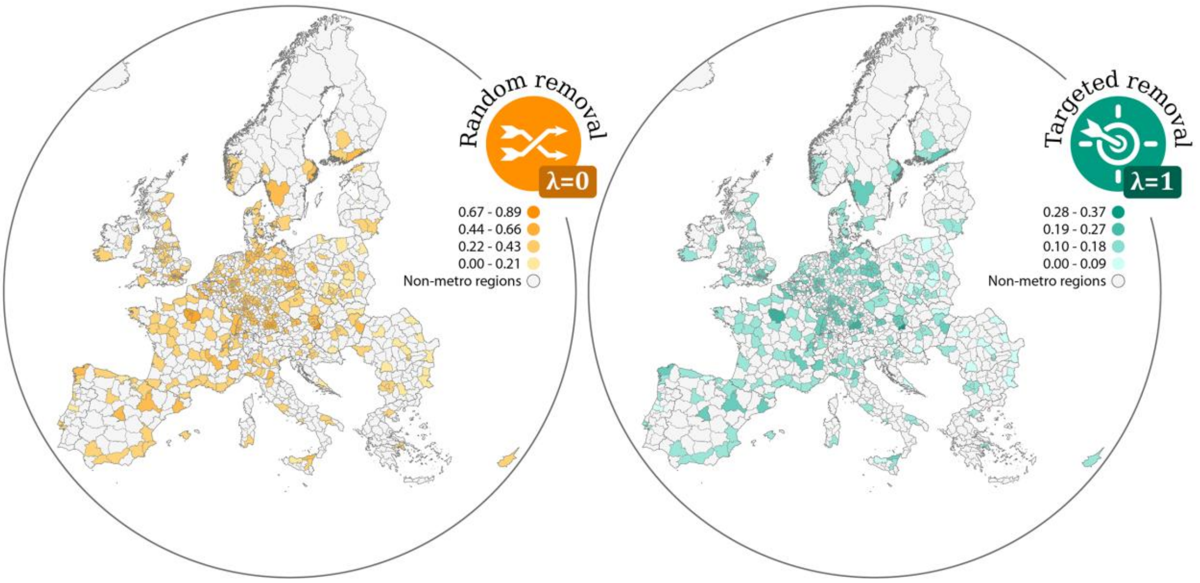
Figure 4. Random and targeted attack curves for selected metropolitan areas across Europe.



Note: The figure shows the tolerance of metropolitan regions against targeted and random elimination based on their technological network (2006 – 2008). The green series of dots refers to targeted, the yellow series of dots refers to random elimination of technologies, while the red dashed line indicates the threshold for the collapse of the giant component. Using the Molloy-Reed criterion, a giant component exists if $\langle k^2 \rangle / \langle k \rangle$ is higher than 2. $\Omega^{\lambda=0}$ and $\Omega^{\lambda=1}$ denotes the amount of eliminations the city can tolerate with a functioning network.

To give an overview of technological network robustness across the 269 European metropolitan regions, *Figure 5* shows maps according to the measured robustness values for λ parameter set to 0 and 1 respectively. That is, the robustness of these regions to the random removal of their technological capabilities, and to the removal of the most frequently combined technological capabilities. While our aim in this paper is not to explore specific shock propagation patters, network robustness with these two parameter values could be considered extreme cases. The latter represents tolerance against a shock affecting the core of the local technological capability base, while the former represents robustness against random disturbance in the capability base. Broadly speaking, the most robust technology networks are found in the European core within the London-Paris-Milan-Munich-Hamburg area, with some additional national capitals such as Madrid. There are exceptions however as Dublin for instance shows relatively low robustness due to its more clustered technology space (*Kogler & Whittle 2018*).

Figure 5. Mapping the geography of technology network robustness across European metropolitan regions.



Next, we test the association between the robustness of local technology spaces and the change of employment rate using the 2008 recession as a test-case. Thus we link employment rate to the network structure of the local technology space as a potential determinant of resilience. *Table 1* presents the findings from the OLS estimation on this relationship. Here, the dependent variable is alternating between employment in all sectors of the local economy (odd-numbered columns), and employment within industry (even-numbered columns). The latter is motivated by the observation that industry relies more on productive knowledge embodied in patents compared with other sectors (*EPO & EUIPO 2019*), consequently it may be more reliant on regions' technological capability base in particular.

Column (1) and (2) show the baseline model with only the control variables. Regarding the controls on socio-economic conditions, we find that the level of gross value added ($\log(GVA)$) has a significant negative coefficient. While this negative coefficient is consistent across specifications, its significance is not. Controls on aspects of the local economic structure indicate first, that related variety (RV) has a positive effect on economic resilience. This is in line with previous findings in the literature on diversification (*Xiao et al. 2018*), and suggests that a higher potential for recombining technological capabilities in new ways makes regions more resilient. This also fits to a broader set of findings showing that the structure of local technology space makes them more resilient in terms of employment (*Rocchetta & Mina 2019*), or inventive activity (*Balland et al. 2015*), and that European regions with a higher share of medium and high-tech industries had higher resilience (*Brakman et al. 2015*). For average clustering (C') within the local technology space, we find a negative and significant effect on resilience, indicating that regions with a tightly-knit core of technological capabilities are more vulnerable to economic shocks. Finally, bridging (B'), aimed to capture that regions may compensate for missing technological capabilities by having an advantageous position in terms of inter-urban knowledge flows (*Balland et al. 2015*), has a consistent positive coefficient across specifications, however it is not statistically significant.

In models (3) and (4) the measure for network robustness (Ω) is introduced with a parameter of $\lambda = 0$, representing the aspect of robustness where the technological capability base of regions is disturbed by the random elimination of capabilities. The coefficient is positive, but significant in particular for the model considering only the employment in industry. The coefficient indicates that those metropolitan regions were more resilient when facing the 2008 crisis that would be able to withstand the elimination a larger number of technological capabilities, chosen at random. Model (5) and (6) test the network robustness for the parameter value of $\lambda = 1$, reflecting how vulnerable a region's technological capability base is to shocks to the most frequently combined technological capabilities. We find that network robustness has a positive and significant effect on resilience, regardless of limiting the dependent variable for industry.

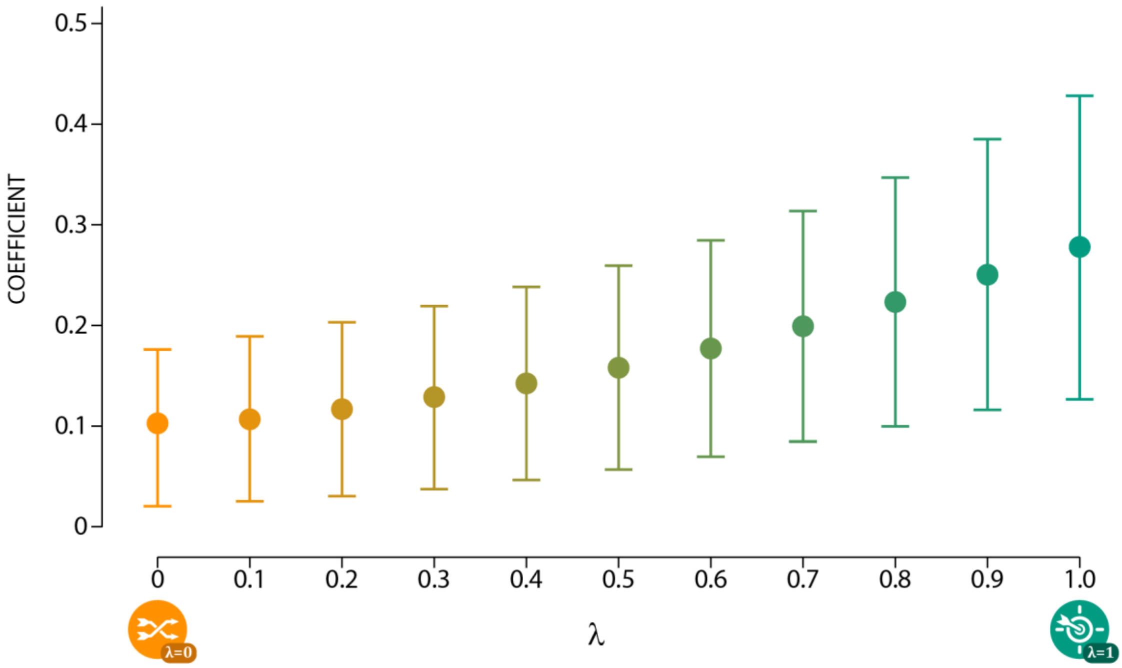
Table 1. Regression results.

	(1)	(2)	(3)	(4)	(5)	(6)
	All sectors	**Industry**	**All sectors**	**Industry**	**All sectors**	**Industry**
$\Omega^{\lambda=0}$			0.0594 (0.038)	0.1046*** (0.036)		
$\Omega^{\lambda=1}$					0.1618** (0.076)	0.2487*** (0.079)
UV	0.0216 (0.02)	0.0023 (0.023)	0.0403* (0.021)	0.0161 (0.026)	0.0436** (0.02)	0.0212 (0.025)
RV	0.0545*** (0.018)	0.0758** (0.03)	0.0208 (0.015)	0.0372 (0.027)	0.0205 (0.015)	0.0388 (0.027)
C'	-0.0035*** (0.001)	-0.0035* (0.002)	-0.0755** (0.034)	-0.0385 (0.048)	-0.0855** (0.034)	-0.0561 (0.052)
B'	0.6184 (0.444)	0.2647 (0.537)	0.5024 (0.480)	0.069 (0.620)	0.4798 (0.467)	0.0583 (0.633)
$\log(GVA)$	-0.0569** (0.027)	-0.0656 (0.039)	-0.0504* (0.028)	-0.0607 (0.041)	-0.0469 (0.028)	-0.0562 (0.042)
$\log(Pop)$	0.0159 (0.048)	-0.0139 (0.033)	0.0494 (0.056)	-0.019 (0.035)	0.0508 (0.055)	-0.0224 (0.035)
$\log(Emp)$	0.0019 (0.038)	0.0065 (0.016)	-0.0371 (0.046)	0.0071 (0.017)	-0.0425 (0.043)	0.0053 (0.017)
Constant	1.2406*** (0.122)	1.4044*** (0.160)	1.2078*** (0.140)	1.4034*** (0.174)	1.1993*** (0.139)	1.3947*** (0.176)
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.214	0.196	0.209	0.191	0.216	0.195
Adj. R^2	0.193	0.174	0.184	0.166	0.192	0.17
Observations	269	269	269	269	269	269

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$

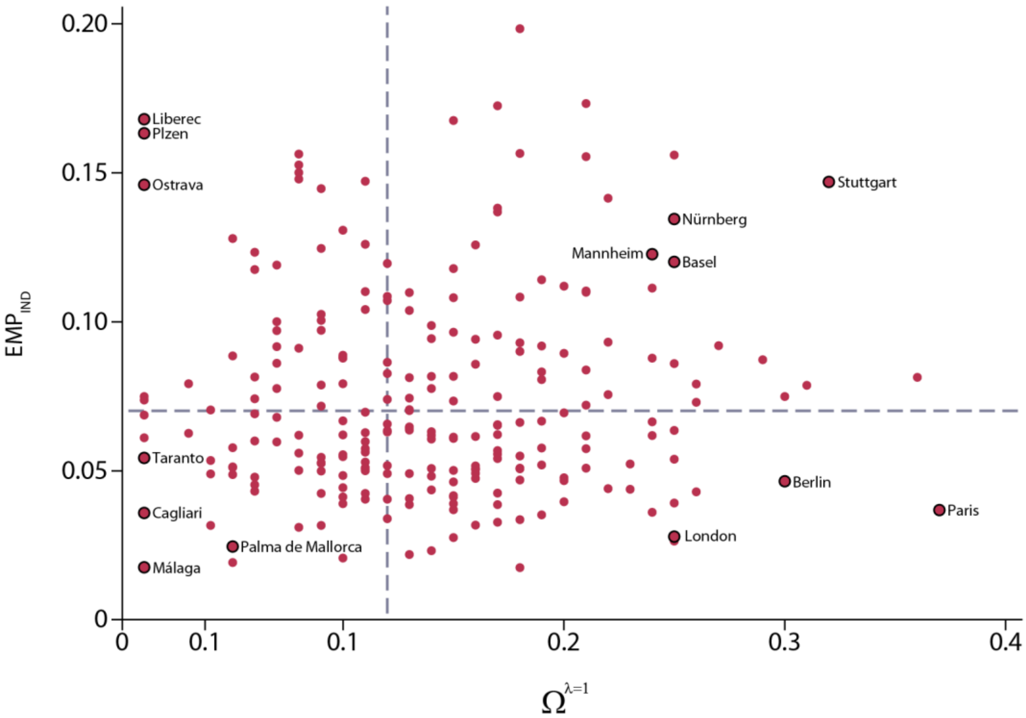
We note that the coefficient of related variety loses its significance in these models, while unrelated variety shows weak significance. What this suggests is that the robustness of the technology network represents structural properties of the local technological capability base that were previously associated with related variety, while unrelated variety likely represents a portfolio-effect when considering a change in total employment in particular. More generally, we find a positive association between network robustness and predicted employment growth in industry for a range of λ parameter values (*Figure 6*), indicating that the network structure of the local technological capability base indeed conditions the resistance of regions to economic shocks. Additionally, the coefficient of network robustness increases with increasing the λ parameter, meaning that this network structure is more consequential for resilience the more a shock is affecting the core capabilities of the region.

Figure 6. Coefficients of technology network robustness for different levels of λ.



Naturally, the robustness of the local technological capability base is not equally concerning for all metropolitan regions. As our results from the regression analysis indicate, such robustness tends to make regions more resilient in terms of employment in industry in particular. Therefore, to assist policy in identifying critical groups of regions when it comes to a shock to the technological capability base, we spit metropolitan areas with median values along the dimensions network robustness (specifically to shocks to the core technological capabilities, $\lambda = 1$) and employment share in industry (*Figure 7*). Regions in the high-high category like Stuttgart, Mannheim and Basel are in a favourable position as they combine a relatively high share of industrial employment with a robust technological capability base. London, Paris or Berlin represent large capital regions exhibiting a high level of network robustness, while having a relatively low share of industrial employment. This makes these regions particularly resilient against shocks to technological capabilities. Regions that score low on technology network robustness but also on employment share in industry, like Cagliari or Málaga, represent cases where regional resilience would likely not stem from a robust technological capability base. Based on this classification, the most disconcerting regions would be those metropolitan areas with a high share of industrial employment but a vulnerable technological capability base, such as Liberec, Plzen or Ostrawa. These, typically traditional industrial regions likely require attention from policy in case of a shock to core technological capabilities.

Figure 7. Technology network robustness and employment in industry across European metropolitan areas.



Notes: gray dashed lines correspond to the median value of each distribution.

5. Conclusion

The economic structure of regions is considered a crucial determinant of the resistance to and the recovery from economic crises (*Boschma 2015, Martin & Sunley 2020*). Still, it is unclear in general which structures are more conducive to regional economic resilience, and in particular how the arrangement of interdependencies in the local capability base leads to more or less resilient regions. In this paper, we propose a way to address this gap by connecting advances in network science to previous efforts to capture the role of technological and network structure of local economies in resilience (*e.g. Balland et al. 2015, Rocchetta & Mina 2019*). By stress-testing the network representation of technological capability bases across 269 metropolitan regions in Europe, we found that regions with a more robust technology network structure were more resistant to the 2008 economic crisis with respect to changes in employment rate in industry in particular. This association held for a range of parameter values representing network robustness to random disturbances to the technological capability base of metropolitan regions, and the targeted elimination of the most frequently combined capabilities. This suggests that network robustness captures a crucial quality of the local capability base with respect to resilience, even when controlling for structural characteristics such as related and unrelated variety, and participation in inter-urban knowledge flows. Finally, the network robustness to the targeted elimination of well-connected technological capabilities was used to sort European metropolitan areas with respect to their vulnerability to disturbances to their core technological capabilities, indicating that traditional industrial regions are particularly challenged in this respect.

This paper takes a first step to integrate research on network robustness and regional economic resilience. However, as any other paper, our study has limitations that should be taken up in future research.

First, we rely on the co-occurrence of technology classes on patent documents to derive local network structures, which admittedly captures only a part of the local capability base. These technological capabilities are more relevant for economic activities of the industry sector (*EPO & EUIPO 2019*), which is reflected in our analysis. As such, the present paper limits its scope to the robustness of frequent knowledge combination patterns within regions to disruptions, and the link of this vulnerability to overall economic performance in terms of employment. Therefore, there is a need to explore network robustness on more detailed network accounts of the regional capability base. Prime candidates in this respect include skill-relatedness networks, that represent similarities in competencies required in different industries, including services, and input-output networks, that allow for in-depth exploration of shock-propagation scenarios. A systematic analysis of metropolitan regions across Europe did not permit us to use such detailed data.

Second, this investigation is limited to the link between network robustness and the resistance to crisis in particular. However the evolutionary interpretation of regional economic resilience puts emphasis also on the renewal of the economic structure (*Martin 2012*), as well as on the ability to develop new growth paths in the long run (*Boschma 2015*). Accordingly, further research could adopt a dynamic approach by tracking temporal changes in the network robustness of the local capability base in response to a crisis, and the effect of local network structure to future diversification patterns. This way one could differentiate between network structures that are conducive of resilience, diversification or both.

Finally, in this paper we stress-tested local technology networks for random failures and targeted elimination of the most frequently combined technological capabilities. Here, further investigation could explore other, or more nuanced scenarios for the elimination process, such as testing for robustness against the elimination of declining technological capabilities, or technologies that are less compatible with green transition. Alternatively, one could explore specific shock propagation patterns to model precise economic crisis events. In this respect this paper tested network robustness in the context of a grand recession, however the anatomy of economic shocks is more diverse (*Martin & Sunley 2020*). We are convinced that the approach proposed in this paper merits further testing along these dimensions.

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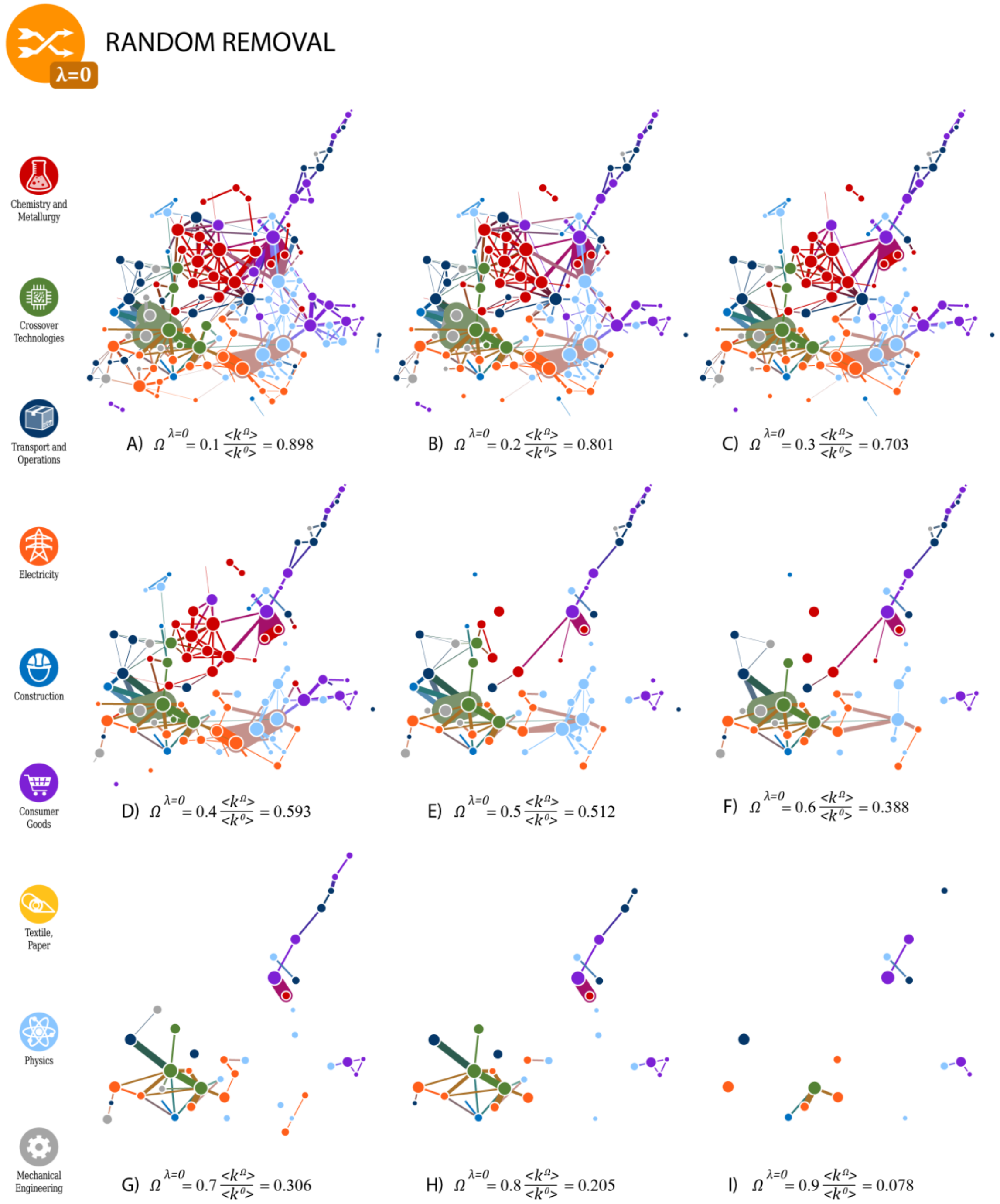
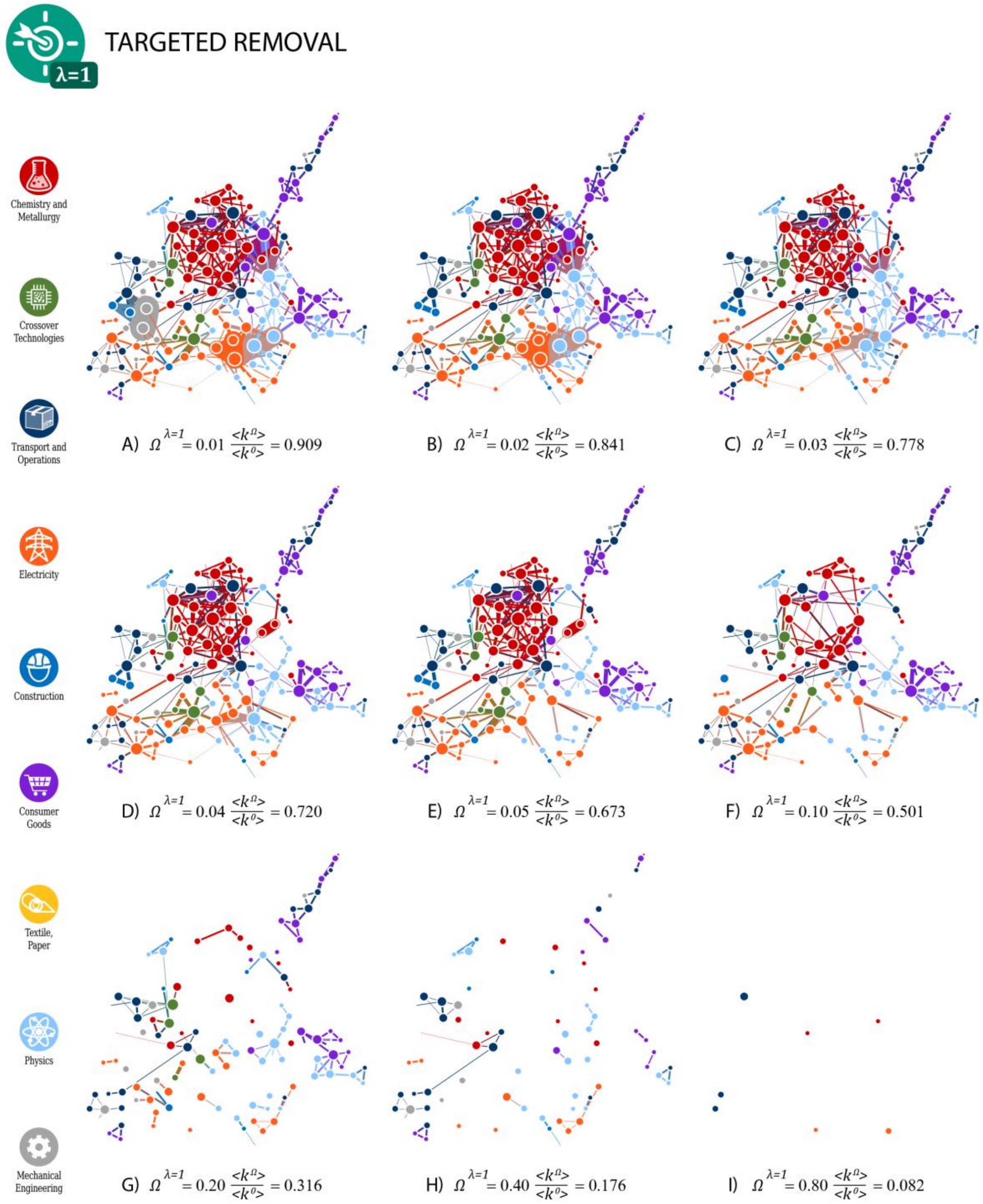
Supplementary Figure 1. Dissolving Dublin's technology space ($\lambda = 0$).



Notes: The colour of the node represents the broad economic sector that primarily utilizes that specific technology class, the size of the node corresponds to the number of patents belong to the given technology class, and the weight of the connection is equal to the co-occurrence of technology classes on patents. $\Omega^{\lambda=0}$ refers to the extent of the random failure, e.g. in sub-figure **(D)** $\Omega^{\lambda=0} = 0.4$ equals to 40 percent of the nodes removed from the network randomly. The stability of the technological space is captured by $\langle k^{\Omega} \rangle / \langle k^{0} \rangle$, which measures the overlap of the edge distribution of the trimmed $\langle k^{\Omega} \rangle$ and the original network $\langle k^{0} \rangle$.

Supplementary Figure 2. Dissolving Dublin's technology space ($\lambda = 1$).



Notes: The colour of the node represents the broad economic sector that primarily utilizes that specific technology class, the size of the node corresponds to the number of patents belong to the given technology class, and the weight of the connection is equal to the co-occurrence of technology classes on patents. $\Omega^{\lambda=1}$ refers to the extent of the attack, e.g. sub-figure **(H)** $\Omega^{\lambda=1}$= 0.4 equals to 40 percent of the nodes removed based on their degree centrality level. The stability of the technological space is captured by $\langle k^{\Omega}\rangle/\langle k^{0}\rangle$, which measures the overlap of the edge distribution of the trimmed $\langle k^{\Omega}\rangle$ and the original network $\langle k^{0}\rangle$.