INSTITUTE OF ECONOMICS
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Közgazdaság- és Regionális Tudományi Kutatóközpont
KÖZGAZDASÁG-TUDOMÁNYI INTÉZET

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Technology network structure conditions the economic resilience of regions

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KRTK-KTI WP – 2022/2

January 2022

https://kti.krtk.hu/wp-content/uploads/2022/01/CERSIEWP 202202.pdf

INSTITUTE OF ECONOMICS, CENTRE FOR ECONOMIC AND REGIONAL STUDIES
EÖTVÖS LORÁND RESEARCH NETWORK (ELKH)
BUDAPEST, 2022

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. We find that European metropolitan areas show heterogeneous levels of technology network robustness. Further findings from 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.

JEL codes: C53, O30, R11

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

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A technológiai képességbázis hálózati szerkezete meghatározza a régiók gazdasági ellenálló képességét

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ÖSSZEFOGLALÓ

A tanulmány 269 európai nagyvárosi térség technológiai képességbázisának hálózati robusztusságát vizsgálja meglévő technológiáik potenciális eltűnésével szemben. Ezáltal szisztematikus bizonyítékot szolgáltat arra vonatkozóan, hogy a 2008-as gazdasági válsággal összefüggésben a hálózat robusztussága hogyan határozta meg e régiók gazdasági ellenálló képességét. Az elemzés a regionális gazdasági hálózati struktúrák és a régiók gazdasági sokkokkal szembeni ellenálló képessége közötti kapcsolat mélyebb megértésével járul hozzá a vonatkozó szakirodalomhoz. A gazdaságföldrajzi vizsgálatokban újszerű hálózattudományi megközelítéssel a cél a régiók technológiai ellenálló képességének stressztesztelése az Európai Szabadalmi Hivatal szabadalmi dokumentumaiban felsorolt CPC-osztályok felhasználásával. Megállapítottuk, hogy az európai nagyvárosi térségek különböző mértékű technológiai hálózati ellenálló képességet mutatnak. A regressziós elemzés további eredményei azt mutatják, hogy a robusztusabb technológiai tudáshálózati struktúrával rendelkező nagyvárosi térségek nagyobb ellenálló képességet mutatnak a foglalkoztatási ráta változására vonatkozóan. A magas ipari foglalkoztatási szinttel, de sérülékeny technológiai képességbázissal rendelkező régiók számára a regionális gazdasági ellenálló képességnek ez az aspektusa különösen fontos.

JEL: C53, O30, R11

Kulcsszavak: regionális gazdasági ellenálló képesség, hálózati robusztusság, nagyvárosi térségek, technológiai-tér

Technology network structure conditions the economic resilience of regions

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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. We find that European metropolitan areas show heterogeneous levels of technology network robustness. Further findings from 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.

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Acknowledgements: The authors are grateful for the comments and suggestions of Balázs Lengyel, Sándor Juhász, Tom Brökel, the participants of the Seminars in Economic Geography series and the vibrant community of Geography of Innovation. The authors appreciate the assistance of Szabolcs Tóth-Zs. with visualisations. Dieter F. Kogler, Gergő Tóth and Adam Whittle would like to acknowledge funding from the Science Foundation Ireland (SFI) under the SFI Science Policy Research Programme (grant No 17/SPR/5324, SciTechSpace). Zoltán Elekes acknowledges financial support from the Hungarian Scientific Research Fund (OTKA K-129207). Dieter F. Kogler and Changjun Lee would like to acknowledge funding from the European Research Council under the European Union's Horizon 2020 research and innovation programme (grant No 715631, TechEvo).

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 level of productivity, 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, as 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 concept 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 (*Simmie & Martin 2010, Martin 2012*), and can 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 (*Christopherson et al. 2010, Simmie & Martin 2010, Pike et al. 2010*), acknowledging 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*).

Yet, 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 (*Hausmann & Hidalgo 2011*, *Neffke et al. 2018*), conditioning the processes of developing new growth paths (*Neffke et al. 2011*), 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. 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 disrupting the local technological capability base. In this way we obtain a measure of network robustness for each European metropolitan region. The measure is then validated by means of regression analysis for the case of the Global Economic Crisis of 2008, where we link 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*.

In short, our findings indicate that European metropolitan regions exhibit a high degree of heterogeneity with respect to the robustness of their technology networks, and regions with a more robust technology network structure showed higher levels of resilience in terms of changes in their employment rate during the economic crisis of 2008. This finding is robust to random and targeted elimination strategies concerning the most frequently combined technological capabilities, and remains even after controlling for established measures of regional economic structure, such as related and unrelated variety.

With these results 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. 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. Combining the state-of-the-art in regional resilience and network robustness research, the paper answers the call for a more detailed understanding on the role that networks play for resilience (*Boschma, 2015*). Thereby the paper joins a broader stream of studies in economic geography broadly defined that deploy network analysis to advance our understanding on collaborative knowledge production (*Ter Wal & Boschma 2009, Broekel et al. 2014, Hermans 2021*), regional diversification (*Neffke et al. 2011, Rigby 2015, Kogler et al. 2017*), and urban economic structure and resilience (*Moro et al. 2021*).

The following section offers a brief overview concerning the empirical literature on regional resilience and network-based approaches to studying regional economies, and connects these with the concept of network robustness. *Section 3* provides details on the datasets used, the proposed novel measure of technology network robustness, and the econometric model specification. Results are described in *Section 4*, while the final section offers a detailed discussion of the findings and further considerations.

2. From regional economic resilience to network robustness

2.1. Regional economic resilience

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 (EEG), 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. 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.

2.2. Relatedness and capabilities

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 (*Brakman et al. 2015*). Moreover, those EU regions that are able to maintain knowledge production in the face of adverse shocks tend to be more resistant in terms of unemployment as well (*Cappelli et al. 2020*). 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 more peripheral places.

Advancements in EEG indicate that the treatment of local economic structure should go beyond the diversity-specialisation dichotomy by considering the relatedness of economic activities (*Kogler 2015, Whittle & Kogler 2020*). Relatedness 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*). Moreover, economic activities are related through sharing various capabilities, which are themselves combined along the production process (*Hausmann & Hidalgo 2011*). Capabilities are factors affecting the production ability of a location, and emerge from a region's resources and sustain its economic activities (*Neffke et al. 2018*). These include property rights, regulations, infrastructure, labour, capital and ameneities for workers (*Bustos & Yildirim 2020*). Knowledge and skills available locally are prominent sources of localized capabilities, contributing to the lasting competitive advantage of regions (*Maskell & Malmberg 1999*). As such, related variety seems to be suited to strike a balance between adaptation and adaptability by both exploiting learning and (re)combination opportunities within the region, and developing new growth paths (*Boschma 2015*).

Nevertheless, there is a tension here. On the one hand, local industries related through similar competencies, shared capabilities or input-output linkages are beneficial for the long-term economic success of a region. This is because related variety offers opportunities for growth (*Frenken et al. 2007*), as well as diversification through innovation and the entry of related economic activities (*Kogler et al. 2017, Xiao et al. 2018*). On the other hand, an economic crisis may also propagate itself easier through a local economy characterized by many related components (*Martin & Sunley 2020*). Indeed, technological relatedness of industries was found to have a positive effect on employment in the very short term (*Cainelli et al. 2019*), and related and unrelated variety of technological specialization were found to have no or negative effect on employment growth in regions of the UK and EU once the average relatedness of technologies was also considered (*Rocchetta & Mina 2019, Rocchetta et al. 2021*). Hence, overall, it is still unclear how relatedness within the local economy shapes regional resilience (*Boschma 2015, Martin & Sunley 2020*).

2.3. Networks and robustness

We propose that this tension can be resolved once local economic structure is considered more explicitly. Networks are of great 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, spatial science and network science has a longstanding relationship (*Ducruet & Beauguitte 2014*), while most recently the emergence of EEG was accompanied by an influx of inspiration and methods from network science (*Broekel et al. 2014*), with respect to cluster knowledge networks and innovative performance (*Ter Wal & Boschma 2009, Hermans 2021*), connections and collaborative knowledge production of places (*e.g., Hoekman et al. 2009, Derudder 2021*), and the relatedness of various elements of the regional economy translating into growth and diversification (for an overview see *Hidalgo 2021*). Still, a network perspective needs to be further developed in economic geography (*Martin & Sunley 2007*), as studying the structure and dynamics regional economies as complex systems relies heavily on a network conceptualization of regions (*Boschma 2015*).

Moving forward we build in particular on the last set of studies, where economies of regions have been characterized as networks of nodes representing for instance industries, occupations, products or technologies, and links represent the level of relatedness between them. Extending *Shutters et al. (2018)*'s argument for urban occupation networks, these network representations reflect a division of labour between the elements of a region's economy, and links reflect solutions to particular co-ordination problems. For technologies in particular, the technology space reveals how frequently specific pieces of technical knowledge (nodes) are combined with one another (links) as evidenced by information from patent documents (*e.g., Kogler et al. 2013, 2017, Boschma et al. 2015*). At the finest resolution these patterns show how particular technological capabilities are being combined to achieve a specific outcomes (*Strumsky et al. 2012*). Hence, the technology space offers a remarkable level of detail on an important set of local capabilities, towards which the literature is otherwise somewhat agnostic (*Bustos & Yildirim 2020*). This admittedly comes at the price of an imperfect representation of other capabilities, including uncodified knowledge. Previous studies approached the overall structure of the local technology space by considering the average degree of shared technological capabilities, and found this to be conducive of resilience in knowledge production in US metro areas (*Balland et al. 2015*), and resilience in terms of employment growth in regions of the UK and EU (*Rocchetta & Mina 2019, Rocchetta et al. 2021*).

We aim to contribute to this emerging empirics by drawing on the network science literature on robustness, referring to the ability of a complex system to carry out its basic function even when some nodes or links are missing (*Albert et al. 2000, Solé et al. 2008, Barabási 2016*). This happens when the underlying network is fragmented into too many disconnected components (*Barabási 2016, Zitnik et al. 2019*), which 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) connected. However, when the extent of node failures passes this threshold, the network falls apart. Regions can be thought of as complex systems of interacting elements (*Martin & Sunley 2007*), that regularly face disturbances ranging from plant closures and technological change, to major economic recessions and natural disasters. For the technology space of a region, such disturbances would imply that the historically formed and region-specific patterns of knowledge co-ordinations would be disrupted. In this setting the threshold then would signify a transition from a wide set of technological capabilities frequently combined with one another, to many small and disconnected clusters of technologies. Finally, this would mean severely disrupting the interdependencies within the local economy, and thus hindering economic performance.

Importantly, the robustness of a network structure depends on the kind of way the nodes are eliminated (*Albert & Barabási 2002*). In particular, random failures are a frequently observed phenomenon in natural networks (*Barabási 2016, Zitnik et al. 2019*). In the context of a regions's technology space such disruption could take the form of obsolescence of technological capabilities as new technical solutions emerge, or the exit of industries relying on specific technological capabilities. Moreover, as technological knowledge tends to be distributed across various actors (*Martin & Sunley 2007*), random failures could also be thought of as declines of firms relying heavily on specific technological capabilities, or combinations thereof. For instance, the largest firms increasingly tend to have a distributed technology profile, extending beyond their core technologies (*Patel & Pavitt 1997*), and so have increased leverage over the technology space of a region. And while technical knowledge, often embedded in individual skills and capital assets, would not disappear *per se*, the crumbling of organisational structures such as firms would still likely render these capabilities to be temporarily inert, until redeployment in new ways can take place. Such ever-present churn of economic agents would then mean that the co-ordination patterns of technical knowledge in a region would be continuously reproduced following disturbances at various scales, translating into resistance before and recovery and renewal after the disruption.

We note that random failure represents an agnostic approach towards the interdependencies between nodes. Yet, it stands to reason that technological and economic shocks could follow along the existing structure of the network. For the technology space of a region this would mean that the inability to rely on one of the locally available technological capabilities would also impact the use of technological capabilities that are frequently combined with the missing one. Hence, disturbances in core technological capabilities that are used by many key actors could trigger a cascade of failures across the technology space of the local economy. In a broader context it is widely documented that natural, social and economic systems are sensitive to such cascades (*Acemoglu et al. 2012*, *Barabási 2016*, *Zitnik et al. 2019*, *Lengyel et al. 2020*). Networks with few nodes having many connections and many other nodes having just a few, such as a technology space with a core of frequently combined capabilities, would be more robust against random disturbances, due to having only a small number of critical technologies with respect to its cohesion. However, such networks are highly susceptible to the failures of these hubs. For these reasons, we expect that the economic resilience of a region would depend on the robustness of its technology space.

3. Data and Methods

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 and EU regions also stress the importance of technological structure in limiting the severity of crisis events (*Balland et al. 2015, Rocchetta & Mina 2019, Rocchetta et al. 2021*). 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.

3.1. Data and spatial unit of analysis

We rely on two different data sources for the investigation. First, we make use of the *Cambridge Econometrics*' European Regional Database (ERD) as a source of economic measures covering the period of 2006-2015. ERD contains a wide range of demographic and economic data for EU 28 countries at the regional level. Second, we use patent data from the European Patent Office (EPO) *PATSTAT* database that covers all European NUTS3 regions to construct our networks of technological capabilities. Patents are a frequently used source of data 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*). At the same time, the drawbacks of patent data are widely acknowledged in the literature (*Ter Wal & Boschma 2009*). Industries vary in propensity to rely on patents for protecting intellectual property (*Graf & Henning 2009*), and patents provide only a partial account on productive knowledge in particular, and locally available capabilities more generally. These drawbacks are offset by a wide coverage of regions across Europe, as well as a unique level of detail on technological capabilities in particular. All patents in the data 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 belongs to. CPC codes are following a strict nested structure, which we use at the 4-digit level, yielding 654 different categories.

We opt for metropolitan areas across Europe as the spatial unit of analysis, because local labour markets tend to be combinations of multiple administrative units, and technological capabilities reflected in patents are more likely to be of relevance for these regions. While our theoretical arguments stand for non-metropolitan regions as well, this choice implies that our empirical findings do not extend to these regions. Nevertheless, our analysis contributes to the understanding of regional resilience, as it complements network-based studies of urban resilience in US metro areas (*Balland et al. 2015, Moro et al. 2021*), with hitherto lacking evidence from the European context. 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 to the commuter belt around the city. This approach adjusts for the potential bias caused by commuting, as the borders of the NUTS3 regions reflect artificial constraints.

3.2. Dependent variable

Regional economic resilience is frequently measured by employment (*e.g. Fingleton et al. 2012*, *Han & Goetz 2015, Rocchetta & Mina 2019*). But 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. In the empirical analysis, we link changes in employment rate to the underlying robustness of the technological capability base. We define our dependent variable as follows:

$$EMPRATE\_CHANGE_i = \left(\frac{EMP_{i,2012}}{POP_{i,2012}}\right) \Big/ \left(\frac{EMP_{i,2006}}{POP_{i,2006}}\right) \qquad (1)$$

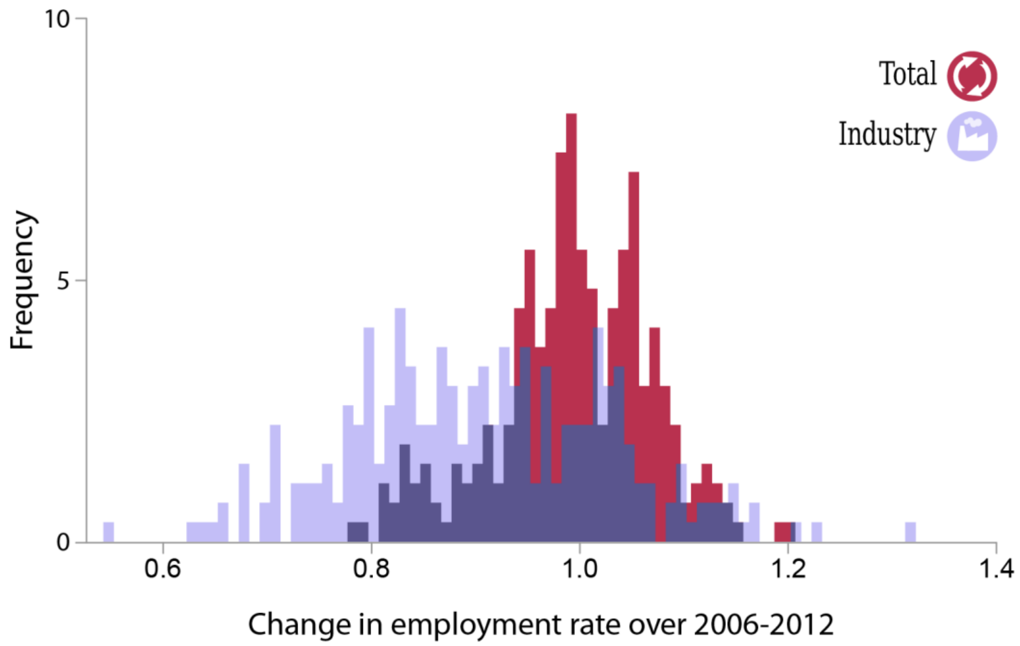
This variable represents the change in employment rate (share of population employed, EMP_i/POP_i) for each European metropolitan region (i) between 2006 and 2012. This timeframe of the dependent variable was chosen because 2006 represents the last year in which no region conceivably experienced the crisis yet, while 2012 was chosen to represent our expectation, based on related studies (*e.g., Moro et al. 2021*), that the pre-crisis network

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

structure of local technologies matters in the early (resistance) stage of the crisis. Restructuring later on would likely alter the configuration of and combinatorial patterns in regions, which requires considering a more dynamic network setting. This however goes beyond the confines of this paper. Robustness tests on alternative time window specifications are provided in *Section 4.3*.

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*).

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



3.3. Independent variable: network robustness

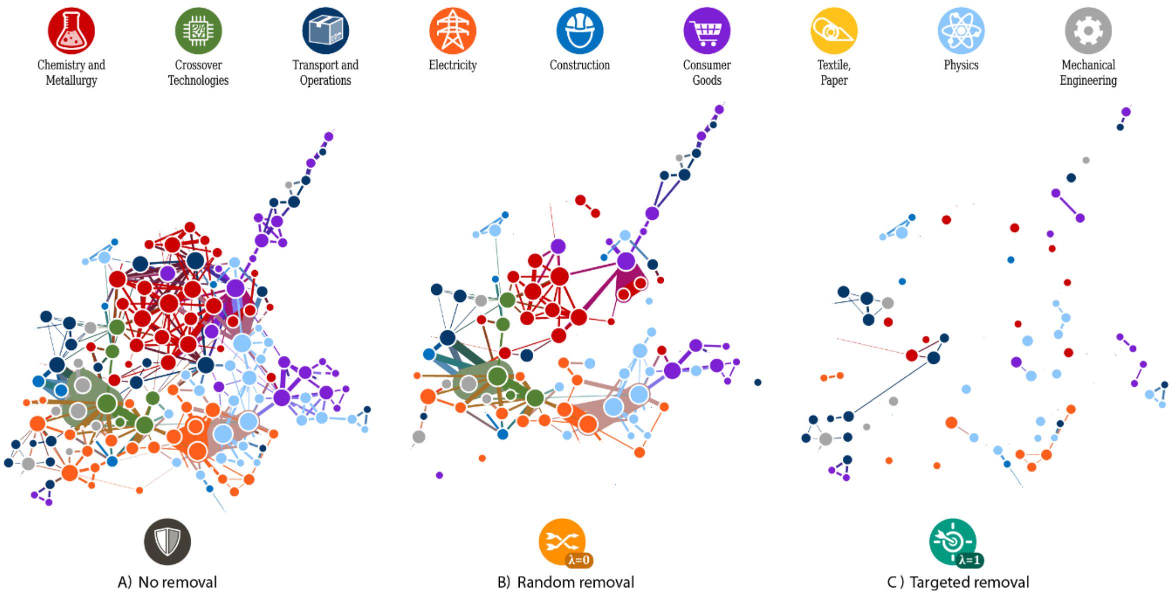
To arrive at our measure of technology network robustness, we first constructed technology networks for each European metropolitan area. In these networks, each node represents a technological capability (one of 654 CPC classes), while the weight of links are proportional to the number of patents that combine the pair of technologies, thus representing the frequency with which the two capabilities are combined in a region. Each network represents local patterns of combination, which means that the existence and weight of a link between the same two technologies varies from region to region. This is important, as links here represent which technologies *are* combined locally, while network construction in regional diversification studies necessarily puts emphasis on what *could be* related to the existing portfolio of the region based on information from other places. Hence, relatedness in our study is considered a more local, than global characteristic of technological capabilities, in line with recent call by *Boschma (2017)* for more exploration on the geographical aspect of relatedness itself.

Next, let Ω denote the amount of node removal that a region's technology network could withstand without being fragmented into many unconnected components. As argued earlier, this would disrupt the ability of a region to achieve previous levels of economic outcomes. 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 $\langle \mathrm{k}^2\rangle$ is the average squared number of links of nodes and $\langle \mathrm{k}\rangle$ 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. 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, ranging on $[0,1]$, to operationalise the extent to which the degree-distribution (*i.e.* the propensity of specific technological capabilities to be combined) is considered in the removal process. λ equals to 1 if technological capabilities with the highest level of degree centrality are removed, while $\lambda = 0$ represents the case of random removal. 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. $\Omega^{\lambda=1}$ and $\Omega^{\lambda=0}$ together define two extremes of network robustness against an economic shock. Note that the aim here is not to simulate explicit shock-propagation patterns but rather to measure the *capacity* of a region to lose technological capabilities through technological change or repeated plant closures.

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 node removal. 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 width 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 magnitude of the average-degree decreases proportionally to the number of nodes removed. In *Subfigure 2C* 40% of the nodes are removed based on the number of connections. We can observe that with 40% of random removal the giant component still exists and technologies still connect to each other, while the same amount of a targeted removal fragments the network into unconnected components (see more detailed illustrations in *SI Figure 1* and *2*).

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



3.4. Control variables

In the econometric estimation we control for a number of structural variables that likely also relate 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, Rocchetta et al. 2021). Measured through entropy decomposition (*Frenken et al. 2007*), *unrelated variety* (UV) measures the entropy of technology codes *between* higher-order groups (1-digit level), and *related variety* (RV) measures the weighted average entropy *within* the group (3-digit level)[2]. Unrelated variety is given by:

$$UV = \sum_{g=1}^{G} P_g \log_2 \left(\frac{1}{P_g}\right) \tag{2}$$

where P_g is the share of local patents falling into a broad technological group S_g ($g = 1, \ldots, G$). *Related variety* is given by:

$$RV = \sum_{g=1}^{G} P_g \sum_{i \in S_g} \frac{p_i}{P_g} \log_2 \left(\frac{1}{\frac{p_i}{P_g}}\right) \tag{3}$$

where $P_g = \sum_{i \in S_g} p_i$ the sum of shares of patents of a 3-digit class i within the 1-digit group S_g. Based on the arguments laid out in *Section 2* we expect positive coefficients for UV and RV. While these variables aim at capturing the global structure of technologies within a region, they rest on an *ex ante* assumption of relatedness by which technology groups are defined. Hence, we also expect that our network robustness provides more accurate account of these overall relatedness patterns.

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 are connected to each other:

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

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

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. The average clustering coefficient ($\langle C \rangle$) is defined by taking the average of node-level clustering values. Since clustering is sensitive to the size of the network (*Barabási 2016*), we normalize these observed average clustering values with those of an Erdős-Rényi random graph (C_{ER}) 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:

$$C' = \frac{\langle C \rangle}{C_{ER}} \tag{5}$$

Third, accessing knowledge flows from other metropolitan areas may compensate for disturbances to the technological capability base and so may contribute to resilience. Hence, following *Balland et al. (2015), bridging* (B') is measured as the normalized betweenness centrality score for each region based on their position in the inter-regional collaboration network. This 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 other regions.

Finally, we include controls for regional socio-economic characteristics. The *level of employment rate* ($EMPRATE$) is included to account for that growth from a higher base level is generally more difficult. *Population* in the metropolitan region (POP) is added to control for urban size and scaling, as evidence from US metropolitan areas indicates a disproportionate increase of both productivity and quality of innovative output with population (*Mewes 2019*). Lastly, the volume of *gross value added* (GVA), measured as the net result of outputs deflated to 2005 prices in Euro, is included to control for the wealth and the quality of economic activities and production factors that were found to be crucial for resilience beyond pure urban size (*Capello et al. 2015*).

Descriptive statistics on and correlation coefficients between these variables are reported in *SI Table 1,* indicating a high correlation between the network robustness measures and related variety in particular. This is expected as both measures aim at capturing the overall structure of local technological capability base. Additionally, the two extreme λ parametrizations of network robustness correlate substantially, however they enter models separately. Subsequent analysis of variance inflation factors (VIF)[3] within the main regression models indicates that multicollinearity should not be a substantial issue in the econometric models, as mean VIF values remain below 3.4 in the models (see individual VIF values in *SI Table 2*). Nevertheless, additional robustness checks are provided in *Section 4.3* that lend support to the main finings.

3.5. Econometric model

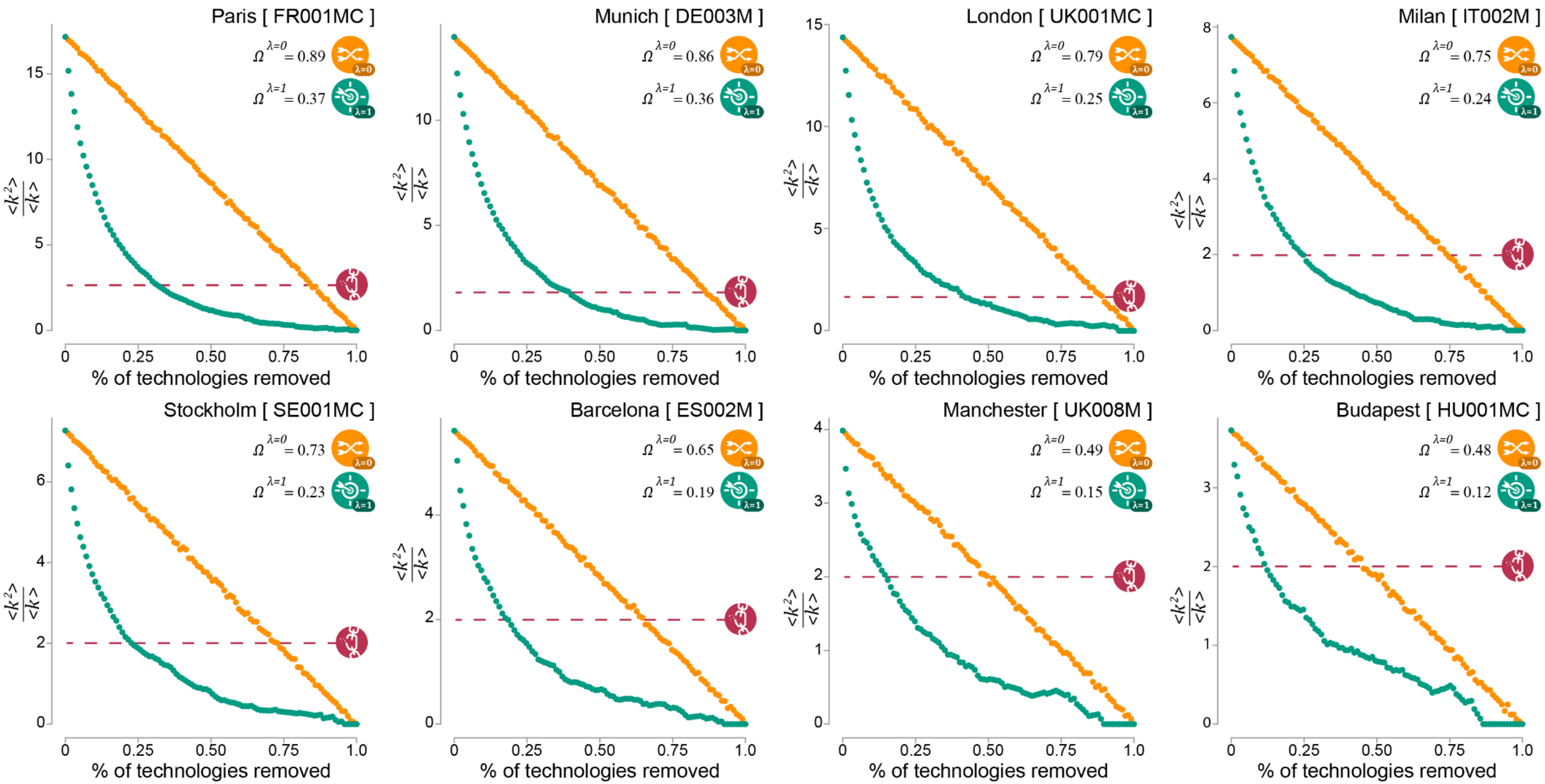
To analyse the association between regional resilience in terms of employment rate change and technology network robustness, we apply a linear regression model. While the unit of observation follows the EUROSTAT classification of the European metropolitan areas, we cannot treat the observations as an 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. Our model specification is the following:

$$EMPRATE\_CHANGE_i = \alpha + \gamma_1 \Omega_i^\lambda + \beta_1[\mathbb{Z}_i] + \beta_2[A_i] + e_i \tag{6}$$

Here $EMPRATE\_CHANGE_i$ captures regional resilience as outcome based on the change in employment rate from 2006 to 2012 for a region (i). The coefficient of Ω_i^λ captures the association between technology network robustness and economic resilience. Separate models are estimated for the two extreme values of the λ parameter concerning node removal. $\mathbb{Z}_i$ is a collection of control variables that describes structural aspects of the technological capability base of a region: related- and unrelated-variety, average clustering, and bridging position, measured for the base year of 2006. A_i stands for a vector of socio-economic control variables: the base level of employment rate, gross value added, and the population of the region. e_i refers to the normally distributed error term of the base year 2006.

[3] VIF measures the linear association between an independent variable and all the other independent variables. A VIF value of higher than 5 warrants further investigation, and a value of higher than 10 indicates a high chance of multicollinearity (*Rogerson 2001*).

Figure 3. Random and targeted removal 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.

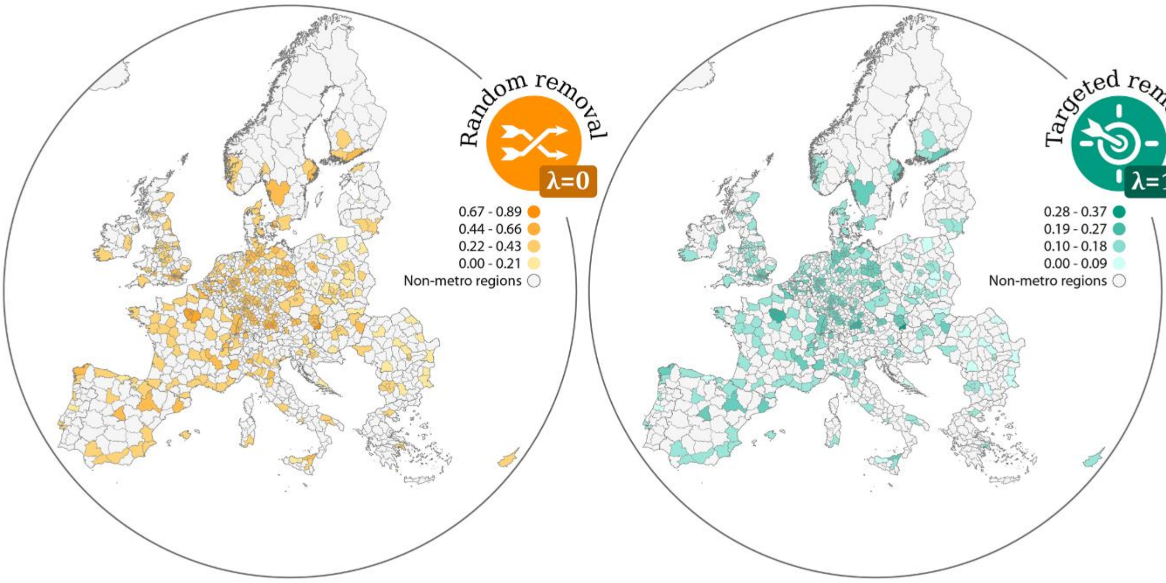
4. Results

4.1. Technology network robustness across metropolitan regions of Europe

First, we present exploratory results on the robustness of technological capability networks for a selection of eight European metropolitan areas to appraise its spatial heterogeneity. Based on *Figure 3* the first noticeable feature of these metropolitan technology networks is that they are robust to a set of random declines in capabilities ($\lambda = 0$) 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, following for instance repeated plant closures or technological change. 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. 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 would need to be removed, while the same network reaches this threshold after removing only 37% of its most connected (most frequently combined) technological capabilities. Consequently the fact that regions tend to have a discernible knowledge profile with some core capabilities (*Kogler et al. 2013, Rigby 2015, Boschma et al. 2015*) is reflected in their structural robustness against economic and technological disturbances. More broadly, this dual characteristic is 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. 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 3*). More broadly, 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 (*Figure 4*). There are exceptions however as Dublin for instance shows relatively low robustness due to its more clustered technology space (*Kogler & Whittle 2018*). Hence, robust technology networks are not a privilege of capital regions. All the more so as regions with high-tech industries like Stuttgart, Mannheim and Basel have a robust technological capability base. Conversely some traditional industrial regions like Liberec, Plzen or Ostrawa have a highly vulnerable technology structure according to our measurement. Finally, while Paris, Berlin, London or Brussels have a high level of network robustness against disturbances to their most frequently combined technologies, most capitals in Central and Eastern Europe are found to be more vulnerable to technological shocks. This seems to be is in line with the documented pattern that the resistance and recovery of capital metro regions in relation to the 2008 crisis was highly uneven in European (*Dijkstra et al. 2015*).

Figure 4. Mapping the geography of technology network robustness across European metropolitan regions.



4.2. The role of technology network robustness during the 2008 recession

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, linking employment with technological network structure as a potential determinant of resilience. *Table 2* 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).

Table 2. Main regression results.

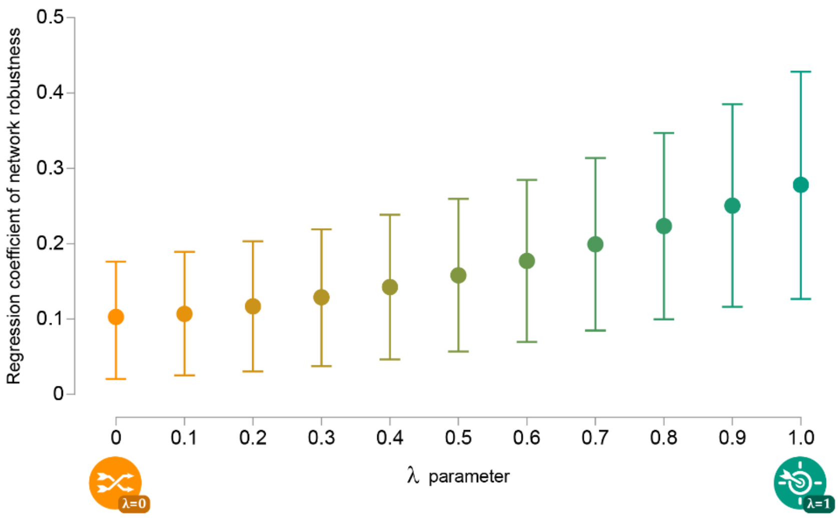
	(1)	(2)	(3)	(4)	(5)	(6)
	All sectors	**Industry**	**All sectors**	**Industry**	**All sectors**	**Industry**
$\Omega^{\lambda=0}$			0.0594	0.1046***		
			(0.038)	(0.036)		
$\Omega^{\lambda=1}$					0.1618**	0.2487***
					(0.076)	(0.079)
UV	0.0216	0.0023	0.0403*	0.0161	0.0436**	0.0212
	(0.02)	(0.023)	(0.021)	(0.026)	(0.02)	(0.025)
RV	0.0545***	0.0758**	0.0208	0.0372	0.0205	0.0388
	(0.018)	(0.03)	(0.015)	(0.027)	(0.015)	(0.027)
C'	-0.0035***	-0.0035*	-0.0755**	-0.0385	-0.0855**	-0.0561
	(0.001)	(0.002)	(0.034)	(0.048)	(0.034)	(0.052)
B'	0.6184	0.2647	0.5024	0.069	0.4798	0.0583
	(0.444)	(0.537)	(0.480)	(0.620)	(0.467)	(0.633)
$\log(GVA)$	-0.0569**	-0.0656	-0.0504*	-0.0607	-0.0469	-0.0562
	(0.027)	(0.039)	(0.028)	(0.041)	(0.028)	(0.042)
$\log(POP)$	0.0159	-0.0139	0.0494	-0.019	0.0508	-0.0224
	(0.048)	(0.033)	(0.056)	(0.035)	(0.055)	(0.035)
$\log(EMPRATE)$	0.0019	0.0065	-0.0371	0.0071	-0.0425	0.0053
	(0.038)	(0.016)	(0.046)	(0.017)	(0.043)	(0.017)
Constant	1.2406***	1.4044***	1.2078***	1.4034***	1.1993***	1.3947***
	(0.122)	(0.160)	(0.140)	(0.174)	(0.139)	(0.176)
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
Mean VIF	3.51	3.51	3.38	3.38	3.12	3.12
R^2	0.192	0.165	0.209	0.191	0.216	0.195
Adj. R^2	0.173	0.146	0.184	0.166	0.192	0.170
Observations	269	269	269	269	269	269

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

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. 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 a larger number of declining technological capabilities. 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 association with resilience, regardless of limiting the dependent variable for industry. More generally, we find a positive association between technology network robustness and predicted employment rate growth in industry for a range of λ parameter values (*Figure 5*), indicating that the network structure of the local technological capability base indeed conditions the resistance of regions to economic shocks.

Figure 5. Regression coefficients of technology network robustness for different levels of λ.



We find that related variety (RV) has a positive association with economic resilience, however the coefficient loses its significance once network robustness enters the model. This suggests first that the learning and recombination potential attributed to related variety in the literature is indeed conducive of resilience, as reflected in previous findings on diversification during crisis (*Xiao et al. 2018*). 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, Rocchetta et al. 2021*), 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*).

Second, the disappearing statistical significance indicates that our measure of technology network robustness captures better the structure and fragmentation of the local technology space. As argued earlier, related variety measured based on an *ex ante* definition of relatedness partially ignores the interdependencies and local specificities of the technological capability base. And while the regional diversification literature made use of information on immediate neighbours of technologies in a technology space, the overall characterisation akin to related variety of such networks is less clear. We argue that this may be a reason why recent work tends to find no significant effect of related variety once a network-wide measure like technological coherence is introduced in models (*Rocchetta & Mina 2019, Rocchetta et al. 2021*). Hence related variety is still in play in our findings, but it is expressed through the robustness of the technology network.

Regarding unrelated variety we find significant positive association in models with network robustness specifically when focusing on employment rate in all sectors. This suggests that the portfolio-effect associated with unrelated variety matters above and beyond the robustness of the technology network, as it captures how diversified the metropolitan technology profile is which may prevent the formation of cascading failures during crisis.

4.3. Robustness checks

We performed a set of checks to test the robustness of our results on technology network robustness. First, as population and GVA in particular has a high correlation, we tested introducing the socio-economic controls in a stepwise manner alongside network robustness

(*SI Table 3 and 4*), which confirms our main finding that robustness to random and targeted elimination of technologies is positively associated with regional resilience. Second, we tested different cutoffs for the starting and end year of the analysis. In particular we rerun our main models considering change in employment rate between 2008 and 2012 (*SI Table 5*), which yielded similar results, except for unrelated variety that lost its statistical significance. Next, we extended the timeframe until 2015, the last year with an almost complete set of observation available in our data (*SI Table 6*). Our main findings remain in place for the case of employment in industry. This is to be expected as the ability to reconfigure the structure of the regional economy becomes a more dominant aspect of resilience over time compared with resistance, *i.e.* the capacity to withstand shocks (*Martin 2012*). Hence, employment dynamics overall will be increasingly determined by factors beyond the pre-crisis structure of technological capabilities. Still network robustness shows positive association with employment rate in industry in particular, where technological capabilities likely play a more important role. Finally, we test controlling for country-specific unobserved characteristics by estimating an entity-demeaned fixed-effect regression (*SI Table 7*). This analysis provided similar results on technology network robustness to our main regression specification with significant, but somewhat smaller coefficients.

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, Rocchetta et al. 2021*). By stress-testing the network representation of technological capability bases across 269 metropolitan regions in Europe, we found considerable heterogeneity in technology network robustness and showed 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 their 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 (entropy of patents over technology classes), and participation in inter-urban knowledge flows. Our findings in the European context complement recent efforts in connecting resilience with urban economic network structure in the US context (*Moro et al. 2021*).

Hence, this paper takes steps towards integrating 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, as discussed earlier, 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. Additionally, technical knowledge codified in patents is likely more relevant in metropolitan areas, compared with other regions. As such, the present paper limits its scope to the robustness of frequent knowledge combination patterns within regions against 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, as well as for a more comprehensive set of places. Prime network candidates 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 take up on these extensions.

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, technological capabilities are typically distributed across a wide range of economic actors and other organisations of the local economy, which we could not observe directly. This permitted us to stress-test local technology networks at a more crude, aggregate level, even though these modelled aggregate shocks are likely rooted in micro-agents. In this respect cluster (knowledge) networks could provide a promising setting to further test network robustness as a determinant of resilience, since there is already considerable knowledge on what determinants drive the formation of these networks, as well as how their structure relates to economic performance (*Hermans 2021*). Further investigation could also explore other, or more nuanced scenarios for the elimination process, such as testing for robustness against the elimination of specific 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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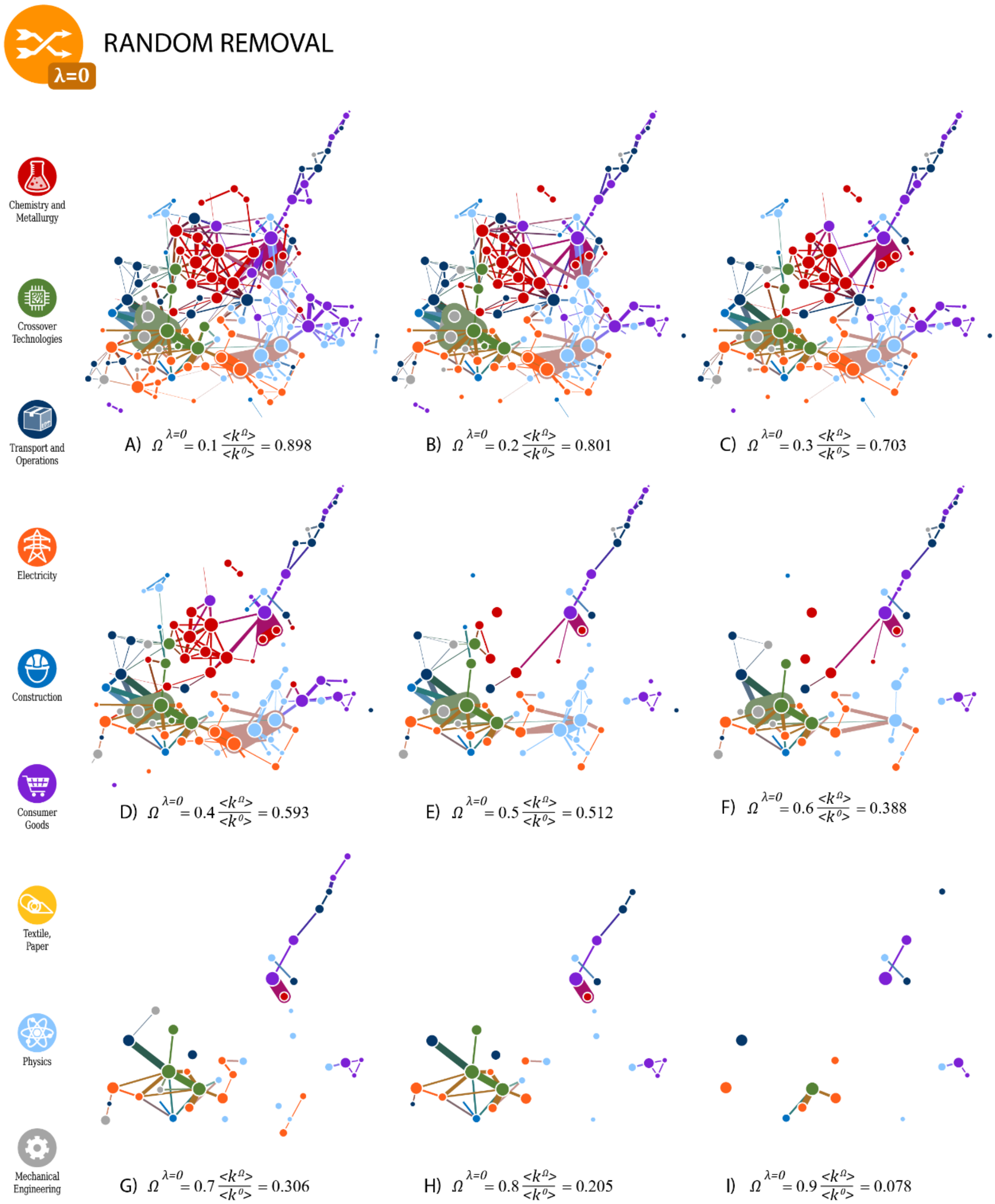
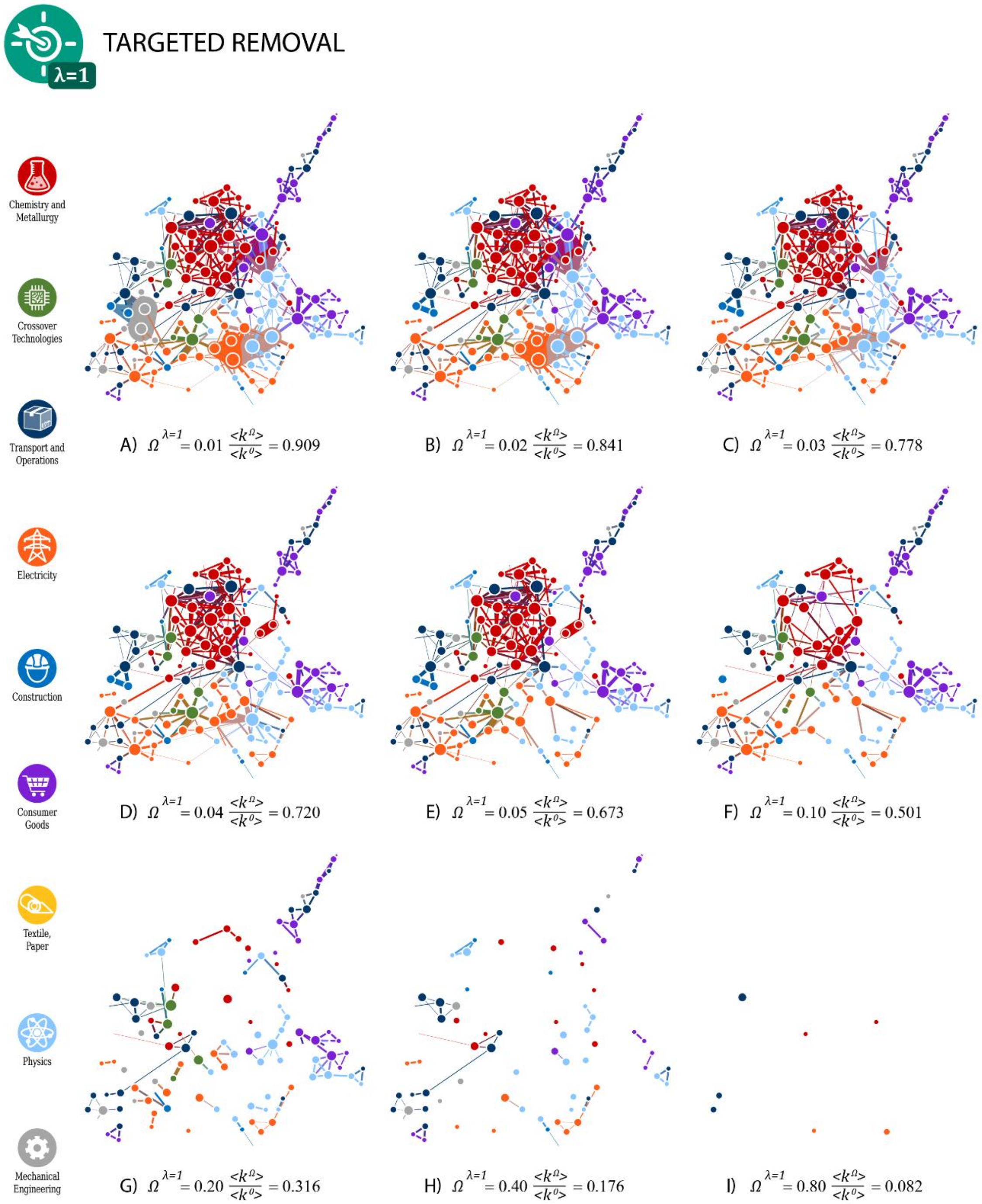
Supplemental Information Figure 1. Dissolving Dublin's technology space ($\lambda = 0$).



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 $\langle k^{0} \rangle$.

Supplemental Information 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 $\langle k^{0}\rangle$.

Supplemental Information Table 1. Descriptive statistics and pairwise correlation of variables.

Variable	Obs.	Mean	Std. Dev.	Min.	Max.
$\Omega^{\lambda=0}$	269	0.430	0.235	0.000	0.890
$\Omega^{\lambda=1}$	269	0.124	0.084	0.000	0.540
UV	269	2.527	0.360	0.722	2.978
RV	269	3.147	1.044	0.000	4.809
C'	269	0.465	0.216	0.000	1.000
B'	269	0.008	0.011	0.000	0.074
$\log(GVA)$	269	9.624	1.003	7.083	13.222
$\log(POP)$	269	6.636	0.724	5.384	9.427
$\log(EMPRATE)$	269	-0.766	0.145	-1.249	-0.392

Correlation matrix

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
(1) $\Omega^{\lambda=0}$	1								
(2) $\Omega^{\lambda=1}$	0.879	1							
(3) UV	0.491	0.365	1						
(4) RV	0.808	0.643	0.678	1					
(5) C'	-0.499	-0.327	0.027	-0.402	1				
(6) B'	0.451	0.392	0.254	0.379	-0.332	1			
(7) $\log(GVA)$	0.663	0.533	0.528	0.706	-0.347	0.447	1		
(8) $\log(POP)$	0.316	0.312	0.224	0.287	-0.138	0.347	0.773	1	
(9) $\log(EMPRATE)$	0.391	0.334	0.219	0.399	-0.288	0.238	0.340	0.057	1

Supplemental Information Table 2. VIF values of variables in models of *Table 2*.

	Model (1) - (2)	**Model (3) - (4)**	**Model (5) - (6)**
$\Omega^{\lambda=0}$		3.38	
$\Omega^{\lambda=1}$			1.83
UV	1.88	1.89	1.91
RV	3.69	4.87	4.41
C'	1.64	1.76	1.64
B'	1.31	1.36	1.35
$\log(GVA)$	7.86	7.92	7.88
$\log(POP)$	4.50	4.50	4.57
$\log(EMPRATE)$	1.35	1.36	1.37
Mean VIF	3.18	3.38	3.12

Supplemental Information Table 3. Stepwise regression results on employment rate change for the 2006-2012 period.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
						Employment change in all sectors						
$\Omega^{\lambda=0}$					0.0803*** (0.020)	0.1551*** (0.025)	0.1100*** (0.021)	0.1465** (0.062)				
$\Omega^{\lambda=1}$									0.2080*** (0.057)	0.3134*** (0.063)	0.2856*** (0.058)	0.2937** (0.141)
$\log(GVA)$		-0.0060 (0.004)		0.0126 (0.080)		-0.0270*** (0.005)		-0.0210 (0.020)		-0.0185** (0.005)		-0.0027 (0.044)
$\log(POP)$			-0.0172** (0.006)	-0.0305*** (0.010)			-0.0278*** (0.006)	-0.0092 (0.025)			-0.0270*** (0.006)	-0.2438 (0.028)
$\log(EMPRATE)$	0.0086 (0.031)	0.0231 (0.033)	0.0135 (0.031)	-0.0123 (0.035)	-0.0422 (0.033)	-0.0238 (0.032)	-0.0531 (0.032)	-0.0320 (0.048)	-0.0315 (0.031)	-0.0081 (0.031)	-0.0387 (0.032)	-0.0345 (0.044)
Constant	1.0000*** (0.024)	1.0712*** (0.061)	1.1191*** (0.049)	1.0655*** (0.060)	0.9271*** (0.030)	1.1779*** (0.059)	1.0900*** (0.470)	1.1703*** (0.122)	0.9440*** (0.028)	1.1275*** (0.059)	1.1080*** (0.047)	1.1190*** (0.108)
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean VIF	-	1.13	1.00	2.44	1.18	1.63	1.21	3.01	1.13	1.36	1.16	2.36
R2	0.003	0.006	0.027	0.036	0.059	0.129	0.117	0.132	0.047	0.089	0.108	0.121
Adj. R2	0.003	0.001	0.02	0.025	0.046	0.119	0.107	0.118	0.04	0.079	0.097	0.108
Observations	269	269	269	269	269	269	269	269	269	269	269	269

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

Supplemental Information Table 4. Stepwise regression results on employment rate change in industry for the 2006-2012 period.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**	**(11)**	**(12)**
						Employment change in industry						
$\Omega^{(\lambda=0)}$					0.1090***	0.2157***	0.1679***	0.1622***				
					(0.032)	(0.039)	(0.032)	(0.056)				
$\Omega^{(\lambda=1)}$									0.2603***	0.4056***	0.4121***	0.3458***
									(0.088)	(0.098)	(0.088)	(0.112)
$\log(GVA)$		-0.0096		0.0406***		-0.0399***		-0.0032		-0.0256***		0.0224
		(0.007)		(0.012)		(0.008)		(0.029)		(0.008)		(0.029)
$\log(POP)$			-0.0389***	-0.0814***			-0.0549***	-0.0578			-0.0529***	-0.0742*
			(0.009)	(0.015)			(0.009)	(0.036)			(0.009)	(0.038)
$\log(EMPRATE)$	0.0920*	0.1146*	0.1031**	-0.0197	-0.0229	-0.0492	-0.0013	-0.0019	-0.0418	-0.0741	-0.0276	-0.0063
	(0.048)	(0.093)	(0.047)	(0.052)	(0.051)	(0.050)	(0.049)	(0.093)	(0.050)	(0.051)	(0.048)	(0.088)
Constant	0.9963***	1.0630***	1.2633***	1.0910***	0.8965***	1.2548***	1.2195***	1.2071***	0.9256***	1.1792***	1.2473***	1.1544***
	(0.037)	(0.093)	(0.074)	(0.089)	(0.047)	(0.092)	(0.710)	(0.146)	(0.044)	(0.092)	(0.072)	(0.108)
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean VIF	-	1.13	1.00	2.44	1.18	1.63	1.21	3.01	1.13	1.36	1.16	2.36
R^2	0.013	0.019	0.071	0.11	0.054	0.119	0.117	0.159	0.044	0.077	0.142	0.152
Adj. R^2	0.009	0.011	0.064	0.1	0.047	0.109	0.107	0.146	0.037	0.067	0.132	0.139
Observations	269	269	269	269	269	269	269	269	269	269	269	269

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

Supplemental Information Table 5. Regression results on employment change in the 2008-2012 period.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	All sectors	**Industry**	**All sectors**	**Industry**	**All sectors**	**Industry**
$\Omega^{\lambda=0}$			0.0526**	0.0796***		
			(0.024)	(0.021)		
$\Omega^{\lambda=1}$					0.1350**	0.1950***
					(0.057)	(0.052)
UV	0. 0061	-0.0140	0.0088	-0.0100	0.0114	-0.0064
	(0.012)	(0.018)	(0.013)	(0.018)	(0.013)	(0.018)
RV	0.0261*	0.0322*	0.0190	0.0215	0.0191	0.0221
	(0.014)	(0.016)	(0.012)	(0.017)	(0.013)	(0.017)
C'	-0.0728*	-0.0400	-0.0623*	-0.0240	-0.0713*	-0.0378
	(0.039)	(0.063)	(0.034)	(0.059)	(0.036)	(0.059)
B'	0.5006	-0.0858	0.3768	0.2732	0.3653	-0.2812
	(0.348)	(0.759)	(0.343)	(0.565)	(0.346)	(0.594)
$\log(GVA)$	-0.0245	0.0059	-0.0267	-0.0025	-0.0234	0.0073
	(0.024)	(0.044)	(0.024)	(0.044)	(0.028)	(0.044)
$\log(POP)$	-0.0070	-0.0506	-0.0061	-0.0493	-0.0097	-0.0545
	(0.018)	(0.038)	(0.056)	(0.038)	(0.018)	(0.038)
$\log(EMPRATE)$	-0.0298	-0.0182	-0.0319	-0.0215	-0.0371	0.0287
	(0.023)	(0.060)	(0.025)	(0.062)	(0.022)	(0.062)
Constant	1.1658***	1.1398***	1.1690***	1.1447***	1.1604***	1.1322***
	(0.126)	(0.176)	(0.130)	(0.179)	(0.130)	(0.181)
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.251	0.179	0.263	0.189	0.270	0.193
Adj. R^2	0.230	0.157	0.240	0.164	0.247	0.168
Observations	269	269	269	269	269	269

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

Supplemental Information Table 6. Regression results on employment rate change in the 2008-2015 period.

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
	All sectors	**Industry**	**All sectors**	**Industry**	**All sectors**	**Industry**
$\Omega^{\lambda=0}$			0.0576 (0.036)	0.0880** (0.039)		
$\Omega^{\lambda=1}$					0.1284 (0. 084)	0.1646** (0.079)
UV	0. 0100 (0.015)	-0.0255 (0.024)	0.0129 (0.016)	-0.0210 (0.024)	0.0150 (0.015)	-0.0190 (0.024)
RV	0.0253 (0.015)	0.0418** (0.019)	0.0175 (0.014)	0.0300 (0.021)	0.0186 (0.014)	0.0333 (0.021)
C'	-0.0826** (0.038)	-0.0742 (0.066)	-0.0710** (0.032)	-0.0566 (0.059)	-0.0811** (0.035)	-0.0724 (0.063)
B'	0.6096 (0.388)	-0.0702 (0.824)	0.4740 (0.372)	0.2773 (0.847)	0.4809 (0.387)	-0.2351 (0.869)
$\log(GVA)$	-0.0461 (0.030)	0.0305 (0.054)	-0.0486 (0.031)	-0.0342 (0.054)	-0.0451 (0.030)	0.0292 (0.055)
$\log(POP)$	-0.0143 (0.025)	-0.0195 (0.050)	-0.0152 (0.025)	-0.0181 (0.038)	0.0117 (0.025)	-0.0228 (0.051)
$\log(EMPRATE)$	-0.0097 (0.042)	0.0868 (0.060)	-0.0121 (0.042)	-0.0832 (0.062)	-0.0167 (0.040)	0.0779 (0.080)
Constant	1.2535*** (0.151)	1.1398*** (0.176)	1.1257*** (0.155)	1.1377*** (0.205)	1.2485*** (0.155)	1.1365*** (0.208)
Clustered SE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.188	0.158	0.200	0.167	0.203	0.165
Adj. R^2	0.166	0.135	0.175	0.141	0.178	0.139
Observations	265	265	265	265	265	265

Note: * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. Data for four Bulgarian and Romanian regions (Varna, Craiova, Constanta and Galati) were not available for 2015.

Supplemental Information Table 7. Regression results on employment change in the 2008-2012 period with country fixed-effect OLS estimation.

	(1)	**(2)**	**(3)**	**(4)**
	All sectors	**Industry**	**All sectors**	**Industry**
$\widetilde{\Omega}^{\lambda=0}$	0.0312**	0.0774**		
	(0.015)	(0.035)		
$\widetilde{\Omega}^{\lambda=1}$			0.0606*	0.1326*
			(0.32)	(0.074)
Constant	0.0031	0.0002	0.000	0.0003
	(0.001)	(0.004)	(0.001)	(0.004)
Country FE	Yes	Yes	Yes	Yes
Regional Controls	Yes	Yes	Yes	Yes
Observations	269	269	269	269

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

To control for country specific characteristics, we estimate the entity-demeaned fixed-effect regressions. First, we take the averages on both sides of our original regression equation (6) for the case of m countries:

$$\frac{1}{m}\sum_{i=1}^{m} Y_i = \frac{1}{m}\sum_{i=1}^{m} \alpha_m + \gamma_1 \frac{1}{m}\sum_{i=1}^{m} \Omega_i^{\lambda} + \beta \frac{1}{m}\sum_{i=1}^{m} [\mathbb{Z}_i, A_i] + \sum_{i=1}^{m} e_i$$

In a simpler form:

$$\overline{Y_i} = \alpha + \gamma_1 \bar{\Omega}_i^{\lambda} + \beta[\bar{\mathbb{Z}}_i, \bar{A}_i] + \bar{e}_i$$

If we subtract it from the original regression equation, the OLS estimate of the parameter $\tilde{\gamma}_1$captures the outcome of network robustness on employment controlling for time-invariant country specific attributes without needing to estimate *m-1* country specific dummies:

$$Y_i - \overline{Y_i} = \gamma_1\left(\Omega_i^{\lambda} - \bar{\Omega}_i^{\lambda}\right) + \beta([\mathbb{Z}_i, A_i] - [\bar{\mathbb{Z}}_i, \bar{A}_i]) + (e_i - \bar{e}_i)$$
$$\widetilde{Y_i} = \tilde{\gamma}_1 \tilde{\Omega}_i^{\lambda} + \tilde{\beta}\left[\tilde{\mathbb{Z}}_i, \tilde{A}_i\right] + \tilde{e}_i$$