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Zoltán Elekes[1,2,*], Gergő Tóth[1,2], Rikard Eriksson[3,2]

[1] Agglomeration and Social Networks Research Lab, Centre for Economic and Regional Studies, Budapest, Hungary.

[2] Centre for Regional Science, Umeå University, Umeå, Sweden.

[3] Department of Geography, Umeå University, Umeå, Sweden.

*Corresponding author: elekes.zoltan@krtk.hu

Abstract: This paper explores how the network structure of local inter-industry labour flows relates to regional economic resilience across 72 local labour markets in Sweden. Drawing on recent advancements in network science we stress-test these networks against the sequential elimination of their nodes, finding substantial heterogeneity in network robustness across regions. Regression analysis with LASSO selection in the context of the 2008 crisis indicates that labour flow network robustness is a prominent structural predictor of employment change during crisis. These findings elaborate on how variation in the self-organisation of regional economies as complex systems makes for more or less resilient regions.

Keywords: local capability base; inter-industry labour flows; skill-relatedness; network robustness; regional economic resilience; regional employment

JEL codes: J21, L14, R11, R23

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1. Introduction

While all regional economies go through periods of crisis and decline, some prove to be more successful than others in coping with such challenging times. This impacts the long-term capacity for growth as the level of success in coping with one crisis conditions the ability of regions to deal with subsequent ones (*Simmie & Martin 2010*). Consequently, the differential growth impact of a crisis slows down convergence and ultimately contributes to persistent spatial disparities. For instance, the 2008 recession put a stop to roughly a decade of regional economic convergence in the EU, driven predominantly by catching up of member states with less developed economies (*EC 2017*).

Knowing more about the capacity of regions to resist and recover from economic turmoil is therefore high on the academic and policy agendas, especially in the expanding literature on regional economic resilience (*Bristow & Healy 2020a*). Despite growing empirical evidence that resilience is highly contingent on the structure of economic activities carried out in regions (*e.g. Hane-Weijman & Eriksson 2017, Martin & Sunley 2020, Fusillo et al. 2022)*, previous studies seldom transcend the specialization-variety continuum. More network-oriented approaches however argue for the fact that shared regional capabilities, rather than structure *per se*, influence resilience (*e.g. Xiao et al. 2018, Kitsos et al. 2023*). This is because regional economies can be considered as (knowledge) networks in which nodes represent specific economic activities, while ties represent the degree of shared productive capabilities or intensity of exchange between them (*Boschma 2015*).

However, our understanding on exactly how local economic capabilities and interdependencies influence regional resilience remains rather limited. To remedy this, there is a need to systematically assess the structural heterogeneity of local economic networks and evaluate how local economic network structures relate to resilience in terms of regional outcomes (*e.g.* employment, output or income). By now a few papers have engaged with this problem in the context of local technology capabilities (*Balland et al. 2015*, *Rocchetta & Mina 2019, Rocchetta et al. 2021, Tóth et al. 2022*), finding that the overall density of relatedness is positively linked with economic outcomes during crisis. Other networks than those of technologies are however underrepresented in the literature, despite that crisis-induced employment effects tend to be more persistent than output effects (*Martin 2012*). The few notable exceptions going beyond technologies also find support for the role of relatedness density (*e.g. Moro et al. 2021, Sánchez-Moral et al.* 2022*, Kitsos et al. 2023*) but mainly concern large urban areas or nation-wide definitions of relatedness, both of which may cause an urban bias in how capabilities are defined and thus how resilience is interpreted. Consequently, there is a need of comprehensive analyses of inter-industry networks in local labour markets across space in general and of labour redeployment potentials in particular.

Drawing on novel methods developed in network science, the aim of this paper is to provide systematic evidence on the link between local industrial network structure and regional economic resilience. This is done by first exploring the heterogeneity in the robustness of local inter-industry labour flow networks against the hypothetical elimination of some of their industries, and, second, by assessing the link between this robustness and the economic performance of regions during the Great recession (2008). Specifically, building on the literatures of evolutionary economic geography, regional resilience and network science (*Section 2*), we use a detailed individual-level panel dataset provided by Statistics Sweden to construct networks based on above-expected labour flows between industries within 72 Swedish functional labour market regions, and measure the robustness of these networks to the sequential elimination of their nodes (*Section 3*). We then test how well this proposed structural measure, compared with alternatives, predicts employment change in the context of the 2008 crisis (*Section 4*), before concluding the paper by discussing implications, limitations and open questions for future research (*Section 5*).

In so doing the paper contributes to the literature on regional economic resilience by detailing how the local self-organisation of labour redeployment flows acts as a determinant of resilience. In particular, we demonstrate the variation in the structural robustness of these flows and that this robustness is a prominent predictor of employment resistance during crisis among established measures of industrial structure. Furthermore, the paper answers the call in evolutionary economic geography for exploring how resilient regions are against the elimination of nodes and links from the network representation of their economic structure (*e.g. Boschma 2015*). Thereby, the paper also connects these literatures more tightly with advancements in network science.

2. Literature

It is a central tenet of economic geography that various economic activities tend to be unevenly distributed in space. This is often attributed to the spatial concentration of these activities (agglomeration) in some places but less so in others, also fostering specialization regardless of whether for instance industries, occupations or technology and scientific domains are considered. Additionally, the location of economic activities is not independent of each other. Instead, some pairs of activities are more likely to be found at the same place compared with others. Such spatial division of labour (*Massey 1995*) gives rise to distinct economic profiles of places, even among regions with the same degree of agglomeration. Besides cost advantages, co-agglomeration patterns are rooted in "untraded interdependencies" that create and maintain the relative competitiveness of cities and regions (*Storper 1997*). These agglomeration economies, or the positive non-pecuniary externalities stemming from co-location, can be attributed to benefits from specialised local suppliers, specialised local labour markets and knowledge spillovers among similar and related activities (*Glaeser et al. 1992*).

2.1. The structure of local inter-industry labour flows

Labour is of particular importance here for at least three reasons. First, empirical evidence on the drivers of co-agglomeration among industries indicates that the relative importance of labour pooling increased over the last century as transport costs decreased (*Diodato et al. 2018*). There is a heterogeneity between services and manufacturing where the former relies more on labour pooling, while value chains in manufacturing remain important (*Ellison et al. 2010, Diodato et al. 2018*). Second, workers are key in the accumulation and transfer of knowledge. The unstandardised, tacit dimension, of knowledge is accumulated through region-, industry- and firm-specific work experience, while even the codified component requires the ability to access, interpret and apply such knowledge by workers. Knowledge is then shared through interactions and mobility. Indeed, firms that are inter-linked by localized networks of job mobility outperform similar firms outside these networks (*Eriksson & Lindgren 2009, Csáfordi et al. 2020*). Additionally, job mobility creates social connections through former co-workers even between firms that experienced no direct labour flows, and the local density of these networks boosts productivity growth in local labour markets (*Lengyel & Eriksson 2017*). Hence, knowledge is not "in the air" even in industry clusters

(*Fitjar & Rodríguez-Pose 2017*) but requires access through being part of such localized labour market networks (*Eriksson & Lengyel 2019*).

Third, labour pooling and variety are not merely a matter of composition, but also of the degree of relatedness between different pairs of industries. Indeed, the job mobility rate as such is not conducive of regional growth. Instead, inflows of workers, whose skills are related to the existing skill composition of workplaces were found to boost firm performance (*Boschma et al. 2009*). Labour linkages also predict industry-region employment growth (*Diodato et al. 2018*) and diversification (*Neffke & Henning 2013*), as well as the productivity and employment growth of regions as compared to very diverse flows (*Boschma et al. 2014*). Hence, labour flows represent an underlying structuring aspect to agglomeration. Since labour tends to be the least mobile production factor even today, knowledge transfer and diversification through this channel remains both path- and place-dependent.

Besides learning, networks of labour flows can be considered to represent worker redeployment potentials. Inter-industry labour flows tend to cut across broader industrial categories, as well as small geographical units (*Guerrero & Axtell 2013*), and these flows form a modular structure in which worker redeployment is more likely within network communities compared with mobility between them (*O'Clery & Kinsella 2022*). This property has been extensively built upon when analysing the coherence and diversification of both regions (*e.g. Boschma et al. 2014, Hane-Weijman et al. 2022*) and firms (*Neffke & Henning 2013*).

What is missing from the above literature on regional labour flow networks is a systematic analysis of the structural heterogeneity across different local labour markets. That is, whether some regions have more robust local labour flow networks than others, thereby having more (or less) conducive structural properties of worker redeployment during structural disturbances. Building on the network robustness literature, robustness here means the rate at which the underlying network of a complex system is fragmented into too many disconnected components (*Barabási 2016, Zitnik et al. 2019*). Considering that regions have various levels of agglomeration, distinctive industrial specialisation following a spatial division of labour, and different degrees of relatedness between co-agglomerating industries, we expect heterogeneity in the network robustness of local inter-industry labour flows.

2.2. Robust inter-industry labour flow networks of resilient regions

Assessing robustness is in and of itself an advancement to our existing knowledge of local labour market structures, but particularly important in understanding regional economic resilience. Considerable effort has been devoted recently in both policy and academia to better understand regional resilience (*Bristow & Healy 2020a*), yet still, it is very much an open question why some regions are more successful in navigating economic turmoil than others (*Martin & Sunley 2020*).

While the concept of resilience has a rich interdisciplinary heritage (*Pendall et al. 2010)*, the literature on regional economic resilience has been converging on an evolutionary interpretation whereby a resilient region shows capacity for both withstanding economic shocks and for developing new growth paths from time to time (*Boschma 2015, Bristow & Healy 2020b*). Accordingly, the conceptual dimensions of resilience include *resistance* to and *recovery* from economic disruption, as well as structural change (*re-orientation*) in response to such disruptions, that may or may not lead to the *renewal* of the regional growth path (*Martin 2012*). How these dimensions translate into desirable levels of output, jobs and income in regions is an indication of resilience, while structures, networks and institutions are main determinants of it (*Boschma 2015*). Key groups of determinants explored in the literature include industrial and business structure, labour market conditions, financial and governance arrangements, and aspects of agency and decision-making (*Martin & Sunley 2020*).

Starting by considering the regional industrial composition along a specialisation-variety axis, specialisation is assumed to offer opportunities for adaptation by exploiting existing local capabilities in relation to a current growth path more effectively, while variety scores higher on adaptability by offering more options for opening up new growth paths (*Boschma 2015*). Indeed, a more diverse industrial portfolio mitigates the impact of idiosyncratic industrial fluctuations in factor supply and output demand (*Doran & Fingleton 2018*), and offers more market options to recombine existing local capabilities during recovery (*Martin & Sunley 2020*). *Fusillo et al. (2022),* for example, recently showed that a diversified industrial structure, compared to technological diversity, characterized the most resilient US metro regions. Second, previous studies have also indicated that regional resilience is related to some key industries or industry segments. Specialising in industries at the forefront of technological change tends to improve regional resilience (*Brakman et al. 2015*), although strategies focusing on these industries may be more effective in urban regions. Moreover, evidence from Sweden suggests that regional employment in sectors associated to the foundational economy were more resilient against a grand recession, although local dependence on these sectors hindered overall regional employment resistance, highlighting the importance of a mix of foundational economy and traded sectors (*Martynovich et al. 2022*).

Third, *Boschma (2015)* conjectured that related variety may strike a balance between adaptation and adaptability by holding the potential for leveraging existing local capabilities in periods of growth, while still allowing for diversification and hence recovery, reorientation and renewal during and after crisis. However, a set of related industries may also boost shock propagation among these industries, exacerbating the impact of even an industry-specific shock (*Martin & Sunley 2020*). Indeed, when analysing the evolution of the Swedish and German shipbuilding industries, *Eriksson et al. (2016)* found that as the focal industry declined, so did many other activities related to shipbuilding. Recent studies also identify a weak negative association between related variety and employment change once the average relatedness of technological capabilities (*Rocchetta & Mina 2019, Rocchetta et al. 2021*), or their network robustness (*Tóth et al. 2022*), are also considered. On the other hand, redeployment potentials to related industries are particularly important in case of involuntary displacement of workers following major plant closures (*Andersson et al. 2020, Hane-Weijman et al. 2018, Nyström 2018*). Hence, tension remains in the literature about how relatedness within the local economy shapes regional resilience.

Furthermore, while regional economies can be regarded as webs of specialized production units, largely dependent on the technologies, skills and tacit knowledge integrated into the process of value creation (*Boschma & Martin 2010*), there is a substantial lack of systematic evidence on how local economic network structures in general, and inter-industry labour flow networks in particular condition the economic resilience of regions. As *Boschma (2015, pp. 714)* noted, "[...] *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 approach put forward by *Boschma (2015)* has in fact been extensively researched in network science in the context of various biological, infrastructural and social networks (*Barabási 2016*), but the connection to regional economic resilience has been forged only in a few instances (*e.g. Gianelle 2014, Tóth et al. 2022*). In the network science literature, robustness is considered to condition 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*). Progressive node or link failures fragment the underlying network of the system, which, above a threshold, translates into a severely compromised outcome level (*Cohen & Havlin 2009*). Given that regions can be conceptualised as complex systems of interacting elements that regularly face disturbances ranging from plant closures and entries and structural change, to major economic recessions and natural disasters (*Martin & Sunley 2007*), there are clear bridges between the two strands of literature. Extending on *Shutters et al. (2018)*'s argument, these networks represent solutions to particular coordination problems in the production of economic output in regions. In the context of local inter-industry labour flows, a node failure can be thought of as an industry-specific shock from plant closure(s) affecting regional employment highly dependent on one (or a few) dominating firms. Or, more generally, a temporary inability of one or more firms in a given industry to change their human capital composition, hence ceasing to be part of labour redeployment flows. Similar cascading failures across a wide range of local industries would hinder previous levels of labour redeployment efficiency and scope, translating into diminishing employment opportunities at the systemic level of a local labour market. In this sense, the robustness of the local inter-industry labour flow networks, capturing the differential capacity of these to tolerate serial disturbances in their industries, would translate into more or less resilient regional economies.

Findings on local networks of technological capabilities indeed indicate that the average degree of shared capabilities is conducive of resilience in knowledge production in US metro areas (*Balland et al. 2015*), and employment growth in regions of the UK and EU (*Rocchetta & Mina 2019, Rocchetta et al. 2021*). Additionally, the network robustness of technology networks in EU metro areas was found to have a positive association with employment during the 2008 financial crisis (*Tóth et al. 2022*). Much fewer studies considered the network structure of local labour markets although the labour market is a main channel through which regional change can come about. Some insights from previous empirical literature suggest that the density of skill-related occupations in US metro areas had a positive association with peak employment during the 2008-recession (*Moro et al. 2021*). *Sanchez-Moral et al. (2022)* also found that Spanish regions with higher density of skill-related industries both resisted and adapted to the 2008 recession compared to less cohesive regions. Finally, and most related to our approach, *Gianelle (2014)* analysed the firm-level labour flow network of the Veneto region in Italy and identified that the robustness of the regional system was highly dependent on which node (firm) was eliminated. Thus suggesting that the regional network structure of labour market interdependencies strongly influence the capacity to manage firm closures.

Despite these important contributions, several caveats remain. First, networks of local technological capabilities are overrepresented in this particular segment of the literature while patent-based information can be considered more accurate in places with intensive patenting activity (predominantly urban areas), and tend to represent particular industries due to the heterogeneity in propensity to patent. Second, and related to the first, many of these findings specifically concern large urban areas, typically using nation-wide projections of relatedness on the regional economies, while smaller regions tend to be neglected despite being most vulnerable to economic shocks. Hence, there is a lack of systematic analysis of inter-industry labour flow networks in local labour markets across space. This is precisely what we take up on in this paper. Based on the above arguments our expectation is that the robustness of local labour-flow networks predicts their economic resilience in terms of resistance during crisis. We test this expectation in the context of Swedish functional labour markets during the recession of 2008.

3. Research design

3.1. Data

We rely on a detailed dataset provided by Statistics Sweden, pooled from multiple Swedish registers. This matched employer-employee dataset covers all workers and workplaces of the Swedish economy between 2002 and 2012 on an annual basis. Workers are linked to one of 264 industries, corresponding to 3-digit industry codes in the NACE Rev. 2 classification system, and one of 72 functional labour market regions through the characteristics of their workplaces. These regions were identified based on commuting patterns, and represent local labour markets.

3.2. Network construction

We rely on labour flow networks to capture the economic structure of these local labour markets. Such networks are considered to reveal the similarity of industries in terms of the worker skills they rely on, as workers are more likely to move between industries where they can still benefit from most of their accumulated skills and expertise (*e.g. Neffke et al. 2017*). The common procedure of constructing skill-relatedness networks is to consider normalized labour flows between industry pairs over a period of time, throughout the national economy. Local labour market structures can be derived by considering industries in which a particular region exhibits relative specialization, as measured by revealed comparative advantage (location quotient greater than one), and normalized labour flows between industry pairs throughout the national economy over a period of time. This way of constructing the network is particularly useful when analysing the related diversification of regions (*Hidalgo 2021*), as information on the relatedness of potential new industries to the existing regional portfolio cannot be assessed on the bases of industries already present. Hence relatedness is inferred based on patterns of other regions across the national economy, and these represent *conceivable* overlaps of worker capabilities between industries.

However, when assessing the robustness of the local industry structure there are arguably two problems, one theoretical and one practical. First, relatedness based on national patterns assumes that these apply uniformly across space. This may hold on average, and may be the case for some industries like basic local services. It may also be misleading in others, such as traded sectors, where the functional specialisation of regions plays a more explicit role. Indeed, calls have been made to apply more "geographical wisdom" when deriving relatedness measures (*Boschma 2017, Fitjar & Timmermans 2017*). Second, from a practical perspective, the local subnetworks of a national skill-relatedness network are instances of the same underlying network structure and essentially represent different stages and sequences of node elimination applied to the same network. This in turn limits the variation across local labour markets structures that are captured by them.

Motivated by these considerations we opt for constructing normalized labour flow networks based only on local labour flows. These networks then more closely represent *actual* location specific labour reallocation between industries, and locally *feasible* transition options for workers. We identify these networks based on local labour flows across 2002-2007, prior to crisis years. Formally two industries are considered connected by labour flows locally, if observed labour flows between them (F_{ij}) exceed what we would expect based on the propensity of these industries to experience labour flows ($(F_{i.}F_{.j})/F_{..}$).

$$SR_{ij} = \frac{F_{ij}}{(F_{i.}F_{.j})/F_{..}} \tag{1}$$

Where $F_{i.}$ is the total outflow of workers from 3-digit industry i, $F_{.j}$ is the total inflow to industry j, and $F_{..}$ is the total flow of workers in the local labour market. To arrive at the final measure of relatedness between industries in the local labour market, as common in research using skill-relatedness (*e.g. Neffke et al. 2017*), we first consider the average of SR_{ij} and SR_{ji} to receive a symmetric measure. Second, the distribution of the raw skill-relatedness measure is strongly right-skewed, as many industry-pairs are weakly related, while few are strongly connected, and so we normalize the measure to have its range between -1 and +1[1]. Hence, in this framework a normalized skill-relatedness of above 0 corresponds to above expected labour flow, which the network representations of local labour markets are based on.

3.3. Network robustness

We then assess the topological robustness of these networks against the sequential hypothetical elimination of their nodes. Specifically, following the approach of *Zitnik et al. (2019)*, we measure a scaled version of the Shannon entropy index of the distribution of industries across isolated components in local networks. As more industries are removed, the local labour flow network fragments into increasingly disconnected components. Depending on the initial network structure, some local labour flow networks fragment more quickly than others, and our final measure of network robustness captures this variation across regions. *Figure 1* offers a schematic overview of the measurement approach.

[1] Following *Neffke et al. (2017)* the normalized skill-relatedness is $\widetilde{SR}_{ij} = \frac{SR_{ij}-1}{SR_{ij}+1}$.

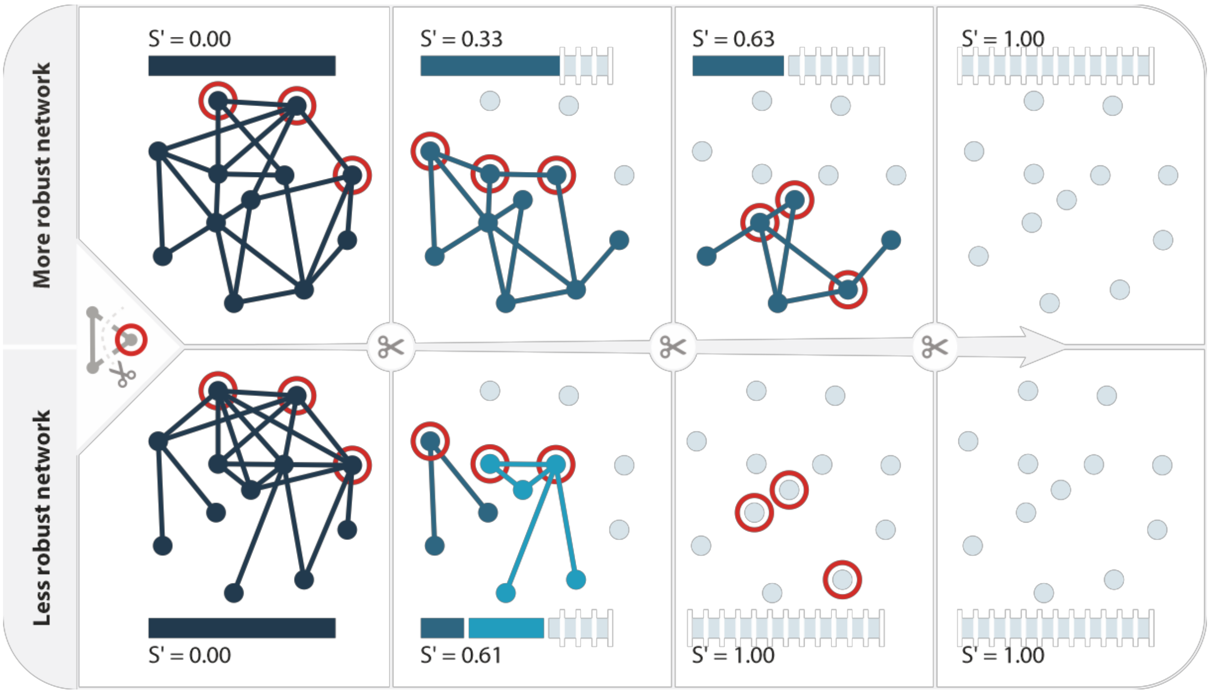


Figure 1. Network components and the robustness of local labour flow networks.

Note: S' indicates the normalized Shannon entropy of the distribution of nodes across disconnected components in the network.

Formally, let us consider the local labour flow network $G_i = (V_i, E_i)$ of region i with N number of industries V_i and M edges E_i. Let f denote the rate of the proportion of the removed industries, which ranges on $f \in [0,1]$. As it is, $f = 0$ captures the initial network state when all industries are present in the region, and there were no node failures. Accordingly, $f = 1$ represents the case when a region's labour flow network becomes completely fragmented. When an industry network G_i undergoes a failure *f*, it is fragmented into multiple components of different sizes. Let $C_{i,k}^{f}$ be the number of nodes that belong to component k in a fragmented network G_i^f with *f* failures. Then we calculate the Shannon entropy of node distribution across the isolated components of $G_i^f\,(C_k)$:

$$S(G_i^f) = -\sum_{k=1}^{K} p_k \log p_k \tag{2}$$

, where K is the number of isolated components in the network at every given failure rate *f*. p_k is the proportion of nodes belonging to the component C_k. To make the entropy measure comparable across regions with different sizes of industry portfolios, we scale Shannon entropy with the log number of industries present in the region:

$$S'(G_i^f) = S(G_i^f)/\log N. \tag{3}$$

To determine the network robustness of each local labour market, we vary the failure rate f on the whole range of the possible values $f \in [0,1]$ with one-per cent steps and then recalculate the scaled Shannon entropy using *Equations (2)* and *(3)*. As a result, we get a robustness curve that captures the degree of fragmentation of the local industry network at each possible failure rate. The final measure of robustness Ω can be calculated as one minus the area under this curve:

$$\Omega(G_i) = 1 - \int_0^1 S'(G_i^f)\, df \tag{4}$$

The measure ranges from 0 to 1, where a higher value refer to a more robust labour flow network structure.

In this paper we use two different industry elimination sequences to stress-test local labour flow networks. As common in the network science literature (*Barabási 2016*), nodes are removed randomly or following the degree sequence of local industries, targeting the most connected first. For random elimination, the average of 500 runs produces our robustness measure. These two approaches represent extreme cases for measuring the capacity of local labour flow networks to withstand shocks, while actual shocks are likely to unfold as a combination of the two. While for the remainder of the paper we present our findings for both random and targeted elimination, we also consider a combined elimination strategy as a robustness check (see discussion of *SI Table 2*).

Figure 2 presents descriptive information on network robustness based on random and targeted elimination. Subfigures *(A)* and *(B)* show that the normalized entropy of industries over disconnected network components increases with the fraction of nodes removed from local labour flow networks. One minus the area under these curves yields the measure of network robustness, reflecting that more robust networks are fragmented slower. According to subfigures *(C)* and *(D)*, regions show heterogeneity in the robustness of their labour flow networks for both random and targeted elimination, but on a much larger range in the case of the latter. Based on subfigures *(E)* and *(F)*, while more densely populated labour markets have more robust networks on average, especially among smaller regions there is considerable variation within the same size range.

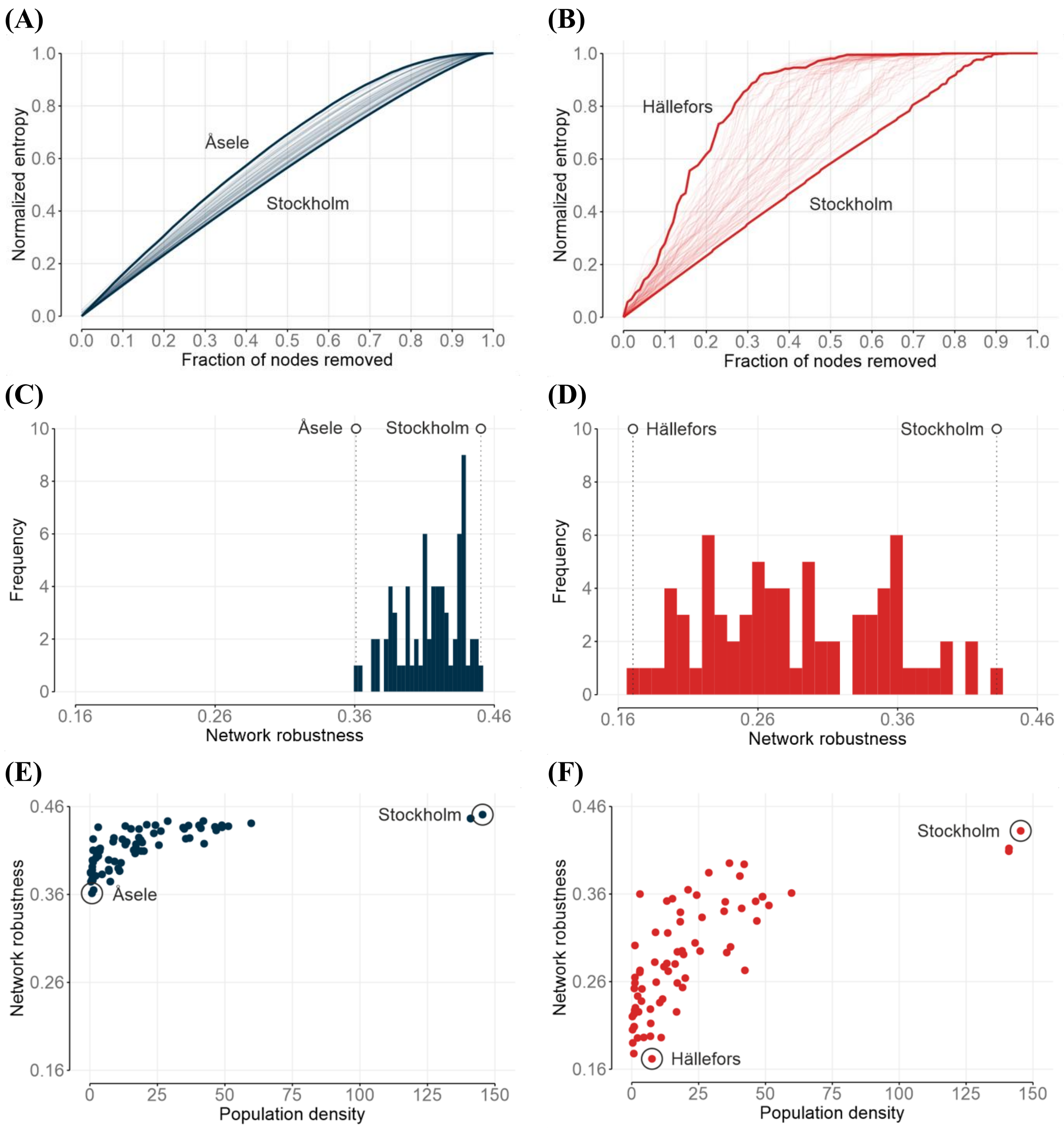


Figure 2. Descriptive information on the robustness of local labour flow networks.

Note: blue represents results on random elimination, while red on targeted elimination.

3.4. Econometric model

We test the association of our measure of network robustness with employment change, a commonly used proxy for regional resilience (*e.g. Martin 2012, Rocchetta & Mina 2019, Rocchetta et al. 2022, Martynovich et al. 2022*), in the context of the 2008 recession. Initially, we use the following ordinary least-squares (OLS) regression:

$$\frac{\mathrm{Emp}_{i,t+s}}{\mathrm{Emp}_{i,t}} = \alpha + Emp_{i,t} + \gamma_1 \Omega(G_i)^{R/T} + \beta_1 [Z_{i,t}] + e_{i,t} \tag{5}$$

, where the dependent variable $\frac{\mathrm{Emp}_{i,t+1}}{\mathrm{Emp}_{i,t}}$ refers to the employment change in region i from the base year of 2007 to upcoming years $t + s \in [2008{,}2012]$. We adjust for the baseline level of the dependent variable with including $Emp_{i,t}$. $Z_{i,t}$ is a collection of control variables and $e_{i,t}$ is a normally distributed error term. Our main variable of interest is denoted by $\Omega(G_i)^{R/T}$, which captures the networks robustness Ω of an industry network G_i against *random* and *targeted* removal of industries (superscript R and T respectively).

Additional variables include *population density* to control for the scaling of economic activities, as larger and more densely populated regions tend to have more economic activities and more dense network representations (*Shutters et al. 2018*). Second, the level of *human capital* in regions is included, measured by the share of workers between 25 and 65 years of age having tertiary education, because higher-educated workers tend to be in a more advantageous labour market status in and out of crisis (*Hane-Weijman et al. 2018*), and more broadly the ability of regions to repeatedly reinvent themselves in the face of economic adversity has been linked to the presence of skilled workforce (*e.g. Glaeser 2005*). Third, various additional measures of local industrial structure have been established in the literature that may be conducive of resilience. Accordingly, we include the absolute diversity and relative regional specialisation of the local industry mix (*Grillitsch et al. 2021*), the economic complexity of regions (*Hidalgo 2021*), and the related and unrelated variety within them (*Frenken et al. 2007*, *Fitjar & Timmermans 2017*) in a set of extended models that aim to assess the relative predictive power of these variables on regional resilience (for a formal definition of these variables see *SI Section 3*). The pairwise correlations of these variables are often high (see *SI Table 1*), which, together with the relatively high VIF values (see in *Section 4*) in the initial regression models indicate a high risk of multicollinearity.

To overcome this potential problem, as well as to identify the key structural predictors of regional resilience, we extend the basic OLS models with a set of *least absolute shrinkage and selection operator* (LASSO) based models. LASSO is most useful in conditions such as ours, with relatively small sample size and many covariates with potential collinearity, and when the relative importance of variables is unclear (*Tibshirani 1996*), as is the case with the variables on local industry structure. In summary, a LASSO selection iteratively adds and removes variables to and from a model, while maximising R^2 and minimising the mean squared error (for a detailed technical description see *SI Section 2*). Since LASSO selection needs multiple runs and offers a number of parametrization options, those variables were included in the final regressions that were selected in at least 85% of the 500 runs of the LASSO variable selection (see *SI Figure 1*).

4. Results

Figure 3 displays the regional distribution of robustness to random *(A)* and targeted *(B)* elimination. In general, the larger city-regions (Stockholm in the east, Malmö in the south and Göteborg in the west) have higher robustness, followed by the smaller regions in the south and regional centres along the northern coast. It is generally the more remote and sparsely populated regions in the north and in middle of Sweden that have the lowest robustness. The regional difference between random and targeted elimination is not stark, instead the difference in scale should be noted. That is, while the most robust regions are as robust to random as to targeted elimination the least robust regions are far more sensitive to targeted eliminations, hence indicating a more specialised and coherent industry-structure.

Based on these observations, and those made in *Section 3*, we see that there is a substantial heterogeneity in the robustness of local labour flow networks across Swedish local labour markets. The question is then whether this network robustness conditions their resilience against an economic shock. To test this, we turn to the regression results on the association of robustness and change in employment in the context of the economic crisis of 2008. This context was chosen because this is the most recent economic crisis event for which we have sufficient data covering the aftermath of the crisis as well. As such, our results pertain to the resilience of regions particularly in the context of a grand recession.

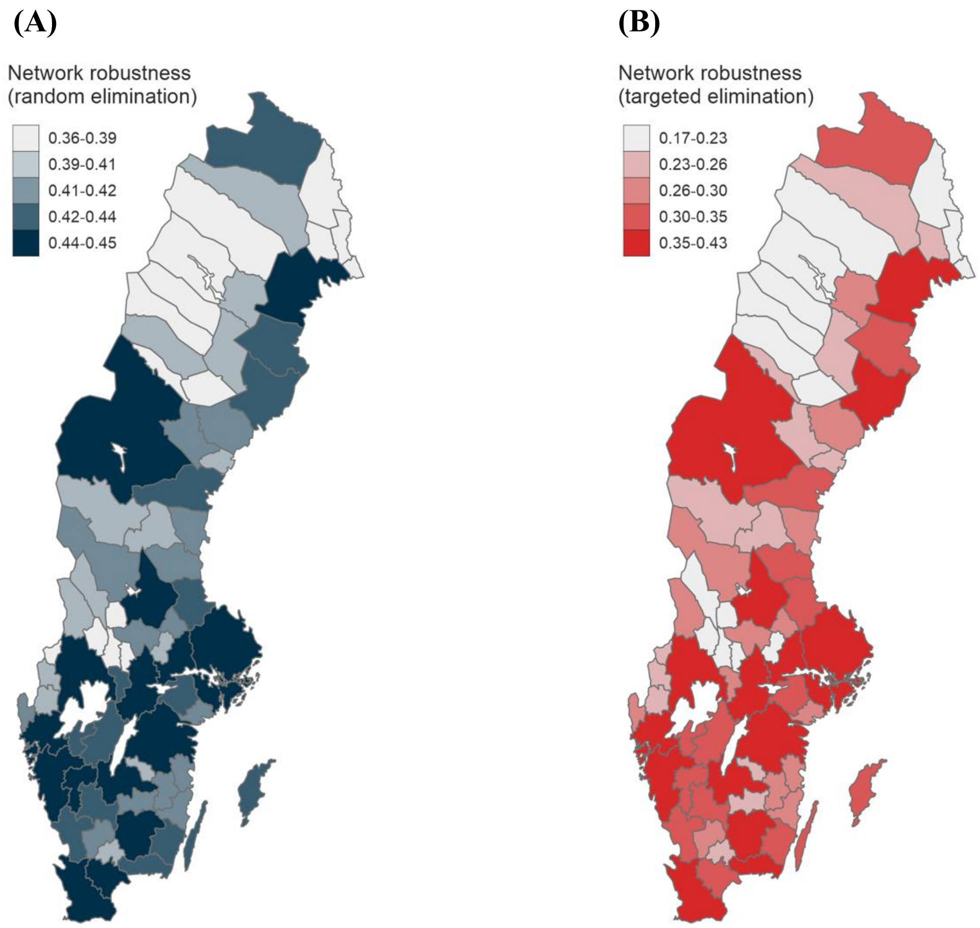


Figure 3. Mapping the robustness of local inter-industry labour flow networks across Sweden.

Note: based on labour flows aggregated across 2002-2007.

Table 1 presents the results of the OLS specification. *Models (1)* to *(4)* provide a stepwise and joint introduction of the control variables, *Models (6)* and *(7)* introduce the network robustness measures (*i.e.* robustness against random and targeted elimination of industries, Ω^R and Ω^T) on their own, while *Models (7)* and *(8)* summarise our main models with both control variables and variables of interest. Control variables show expected signs with the exception of regional employment in *Models (1)* and *(4)*. This is due to the fact that this variable picks up on structural characteristics of the region as well. Once additional controls and structural variables enter the models, it takes on the expected negative sign, following the classical finding that higher growth rates are more difficult to attain from a higher base.

Population density shows the expected positive sign, although it remains statistically not significant when other variables are present in the models. Finally, human capital shows a significant positive association across models, indicating that indeed regions endowed with better educated workers tend to have a higher employment change rate during crisis.

Table 1. OLS regression results.

	Dependent variable: employment change 2007-2012							
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
$\log_{10} REGEMP_{2007}$	0.027*** (0.007)			0.002 (0.015)			-0.076* (0.038)	-0.027 (0.026)
$POPDENS_{2007}$		0.001*** (0.000)		0.000 (0.000)			0.001 (0.000)	0.000 (0.000)
$HUMCAP_{2007}$			0.394*** (0.088)	0.340** (0.150)			0.355** (0.146)	0.290* (0.154)
Ω^R_{2007}					0.882*** (0.219)		1.996** (0.903)	
Ω^T_{2007}						0.316*** (0.075)		0.334 (0.252)
Constant	0.861*** (0.031)	0.964*** (0.006)	0.879*** (0.022)	0.880*** (0.043)	0.661*** (0.104)	0.885*** (0.025)	0.369 (0.235)	0.917*** (0.051)
# Region	72	72	72	72	72	72	72	72
R^2	0.167	0.120	0.225	0.228	0.189	0.199	0.280	0.248
Adjusted R^2	0.156	0.107	0.213	0.194	0.177	0.188	0.237	0.203
F-Statistic	14.08***	9.53***	20.27***	6.69***	16.26***	17.43***	6.52***	5.51***

Note: standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Turning to our main variables of interest, we find that the robustness of the local labour flow network against both random and targeted removal of industries has a significant positive association with employment change. This indicates that regions with a higher capacity to withstand disturbances to the local capability base of their workforce tend to exhibit higher economic resilience in terms of resistance. This is because due to labour pooling across industries, removing an industry is likely to leave others still relying on similar worker capabilities. Additionally, workers belonging to industries more isolated in the local labour flow network have fewer redeployment options to make in case of job loss in the wake of the crisis. Crucially, both of these interpretations depend on the network structure of the local industries. In this way our findings are in line with those of recent contribution on local network structures and resilience (*Moro et al. 2021, Tóth et al. 2022*), while extending on their analysis by considering the regional industrial structure in particular, as well as by moving beyond the analysis of metropolitan regions.

As we discussed in *Section 3*, there is a high correlation among the covariates, and average VIF values in the baseline OLS models exceed the tolerable range (*Model 1* of *Table 2* and *3*). This potential problem of multicollinearity further increases once we include alternative measures proposed in the literature to capture aspects of local industrial portfolios. To mitigate this problem, we turn to the results of the LASSO inference that identifies the most stable predictors of the outcome variable in case of a small number of observations compared with a larger number of potentially collinear predictors. In *Table 2* and *3* we present the results of this approach for robustness to random and targeted removals respectively. In both cases *Model (1)* repeats the main model from *Table 1*, and in *Model (2)* additional structural variables are included in an OLS specification. *Model (3)* reports the coefficients obtained from LASSO inference, *Model (4)* shows the variables that were selected by the LASSO inference as the main predictor of employment change, while *Model (5)* reports the coefficients obtained from an OLS specification with LASSO-selected variables. As reported in the two tables, mean VIF values in these final models are well within the acceptable range.

The LASSO selection indicates that the robustness of local labour flow networks is the most consistently present predictor among all variables considered (*SI Figure 1*). In the OLS models with LASSO-selected variables we find that the positive association between robustness and employment change holds, meaning regions with a propensity for fragmentation in local worker redeployment pools fared worse during the 2008 recession. We also find that robustness to random elimination of industries has a greater coefficient compared with that of removing the most connected industries. This is admittedly unexpected, however one must consider that the relative importance of random and targeted robustness depends on the interplay between the local network structure and how an economic crisis unfolds over it. While early on, shock propagation likely follows through related links, it does not necessarily follow the degree distribution of industries, especially when the outcome in terms of employment change is aggregated across years.

Table 2. LASSO inference and LASSO-selection-based OLS results for random removal.

	Dependent variable: employment change 2007-2012				
	(1) OLS (baseline)	**(2)** OLS	**(3)** LASSO inference (adaptive)	**(4)** LASSO selection	**(5)** OLS with LASSO selection
$\log_{10} REGEMP_{2007}$	-0.076* (0.038)	-0.004 (0.063)	-0.022 (0.065)		
$POPDENS_{2007}$	0.001 (0.000)	0.000 (0.000)	0.000 (0.000)		
$HUMCAP_{2007}$	0.355** (0.146)	0.100 (0.163)	0.107 (0.150)		
Ω^{R}_{2007}	1.996** (0.903)	2.195** (0.864)	2.299** (0.925)	X	1.725*** (0.434)
$RELVAR_{2007}$		-0.041 (0.041)	-0.046 (0.038)	X	-0.066** (0.026)
$UNRELVAR_{2007}$		-0.147 (0.140)	-0.142 (0.154)		
$THEIL_{2007}$		0.002 (0.001)	0.002 (0.002)	X	0.002* (0.001)
DIV_{2007}		0.017 (0.017)	0.015 (0.020)		
RSR_{2007}		-0.005 (0.010)	-0.002 (0.010)		
ECI_{2007}		0.081 (0.070)	0.083 (0.061)	X	0.092** (0.035)
Constant	0.369 (0.235)	0.560 (0.386)			0.423*** (0.125)
# Region	72	72	72	72	72
R^2	0.280	0.462			0.446
Adjusted R^2	0.237	0.374			0.413
Mean VIF	13.84	29.88			3.69
F-Statistic	6.52***	5.25***			13.47***

Note: standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Table 3. LASSO inference and LASSO-selection-based OLS results for targeted removal.

	Dependent variable: employment change 2007-2012				
	(1) OLS (baseline)	**(2)** OLS	**(3)** LASSO inference (adaptive)	**(4)** LASSO selection	**(5)** OLS with LASSO selection
$\log_{10} REGEMP_{2007}$	-0.027 (0.026)	0.046 (0.066)	0.026 (0.072)		
$POPDENS_{2007}$	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)		
$HUMCAP_{2007}$	0.290* (0.154)	0.064 (0.170)	0.067 (0.161)		
Ω^T_{2007}	0.334 (0.252)	0.216 (0.249)	0.267 (0.283)	X	0.280*** (0.097)
$RELVAR_{2007}$		-0.031 (0.042)	-0.036 (0.042)		
$UNRELVAR_{2007}$		-0.111 (0.146)	-0.105 (0.153)		
$THEIL_{2007}$		0.002* (0.001)	0.002 (0.002)	X	0.003*** (0.001)
DIV_{2007}		0.014 (0.018)	0.011 (0.019)		
RSR_{2007}		-0.003 (0.010)	-0.000 (0.020)		
ECI_{2007}		0.071 (0.073)	0.074 (0.068)	X	0.091** (0.040)
Constant	0.917*** (0.051)	1.075*** (0.358)			0.874*** (0.026)
# Region	72	72	72	72	72
R^2	0.248	0.413			0.377
Adjusted R^2	0.203	0.316			0.350
Mean VIF	7.65	29.12			1.67
F-Statistic	5.51***	4.29***			13.72***

Note: standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

With respect to other variables on the industrial structure of regions we find first that the Theil-index ($THEIL_{2007}$) is consistently selected as a predictor that captures regions that are more specialised than the average in the Swedish context. Second, local labour markets with a more complex industrial structure (ECI_{2007}) fared better during the crisis. This is an interesting and novel finding, extending on previous results showing that regions branching into more complex occupations also had a faster employment growth after the recession (*Hane-Weijman et al. 2022*). Complexity thus seems to be associated with resilience, at least in the Swedish case. It is important to note though that this finding is sensitive to including large metro regions in the sample (see below). Finally, we find that $RELVAR_{2007}$ is a

LASSO-selected predictor of employment change when considering network robustness especially to random elimination (and is barely below the cut-off for inclusion in the targeted case). It has a similar sign compared to other instances when an entropy-base variety measure is included in models along with network-based measures of relatedness (*e.g. Rocchetta & Mina 2019, Rocchetta et al. 2021, Tóth et al. 2022*). That is, the measure based on explicit relatedness captures the conceptual core of related industries with shared local capability base. Further, since industrial classifications tend to classify together activities using similar technologies, this coefficient may express the downside of relatedness during crisis in terms of shared supplier linkages. To sum up, the LASSO-selection models return a set of variables representing existing approaches to local economic structure in terms of industrial specialisation ($THEIL_{2007}$), content (ECI_{2007}) and interdependencies (Ω_{2007}), among which the latter is a prominent predictor of employment outcomes during crisis. It should also be noted that despite including only a limited number of conceptually relevant variables, R^2 is almost doubled in both cases compared to the initial OLS regressions.

To test the robustness of our findings, we ran alternative specifications that lent support to our main conclusions drawn here. First, the metro regions in our sample have an outstanding structural diversity in terms of industries, which makes them very different from the rest of the sample (see *Figure 2*). To test whether these urban areas drive our results, we reran the models presented in *Tables (2)* and *(3)* after excluding these regions (*SI Table 3*). The findings of the main models remained in place with the exception that the ECI_{2007} lost its statistical significance, likely due to the fact that complex economic activities tend to concentrate in large cities (*Balland et al. 2020*). Second, our dependent variable covers the period 2007-2012, with which we aim to capture the early stage of the crisis and its immediate aftermath but of course choosing the end of the resistance period is up for debate. Hence, following *Martynovich et al. (2022)* we tested an alternative period in which employment change between 2007 and 2009 is considered (*SI Table 4*). As the main employment effects were expressed in 2008 and 2009, this would correspond to a conservative estimate of the resistance stage during this particular crisis. Results of this test leave our main findings in place. Third, the capacity to tolerate random and targeted removal of nodes are two extreme cases for these local networks. Therefore in a further test we combined targeted and random removal (50% chance for either in a series of removals), leading to similar findings (*SI Table 2*).

5. Conclusion

In this paper we proposed an approach to engage with which arrangements of interdependencies between local economic activities are conducive of resilience by drawing on advancements in evolutionary economic geography and the rich toolbox on network robustness developed in network science. Thereby, the paper provided hitherto scarce systematic evidence in the context of local labour markets of an entire national economy on the link between local industrial network structure and regional economic resilience. Specifically, building on rich administrative data covering the universe of workers in Sweden, we stress-tested 72 local labour markets against the progressive hypothetical elimination of industries from their local inter-industry labour flow networks.

The explorative part of the analysis indicates a substantial heterogeneity between the regional labour flow networks in terms of robustness to random disturbances as well as the targeted removal of their most connected industries. Since these networks represent worker redeployment potentials within the context of local labour markets (*Gianelle 2014, O'Clery & Kinsella 2022*), this finding indicates that the same economic shock would isolate workers into disconnected segments of the labour market more easily in some regions compared with others. Importantly, we find that this goes beyond being a matter of regional size, stressing instead that emergent local solutions to coordinating labour across economic activities yields structural strengths and vulnerabilities even among otherwise similar regions. Thereby we advance previous studies based on nation-wide relatedness (*e.g. Sanchez-Moral et al. 2022*) or a specific regional case (*Gianelle 2014*). Since redeployment potential is crucial in reemployment after involuntary loss of work (*Hane-Weijman et al. 2018*), from a policy perspective this makes it imperative to have a clear understanding of the existing structure of local labour flows so that the fragmentation of redeployment potentials during crisis can be mitigated with targeted retraining programs that counteract workers being isolated in disconnected segments of the labour market.

Moreover, we find that regions where inter-industry labour flows constitute a network that fragments slower into disconnected components when facing a series of economic disturbances fared better in terms of employment during a grand recession. In such local labour markets, workers are comparatively less likely to be isolated into a particular segment of related activities as an asymmetric crisis unfolds. The paper thereby advances the conceptualisation of regional economies as complex systems (*Martin & Sunley 2007*) by showing that the self-organisation of local labour markets into labour flow networks of different structure is linked to regional economic performance during crisis. The findings from LASSO selection models also show that network robustness is a prominent predictor of employment change among several structural measures of local economic activities, indicating the importance of region-specific arrangements of labour redeployment potentials. Therefore, while structural features of regional economies are a well-established determinant of regional resilience (*Martin & Sunley 2020*), there is more to this structure than the distribution of workers across economic activities, or relatedness based on national aggregates between them would indicate.

In highlighting the regionally varying structural features of labour redeployment potentials our paper contributes to an emerging research stream exploring the role that local economic network structures play in regional economic resilience (*e.g. Balland et al. 2015, Moro et al. 2021, Tóth et al. 2022, Kitsos et al. 2023*). By focusing on labour market realignments rather than output our findings push the existing frontier by elaborating on the variation that exists in the self-organisation of regional economies as complex systems through inter-industry labour flows and how this makes for more or less resilient regions.

However, our study has limitations that also correspond to open questions in the literature. First, our proposed measure of robustness was derived from a static network defined by normalized labour flows prior to the crisis. The conceptual breadth of regional economic resilience includes the ability of regions to develop new growth paths and not only withstand a shock (*Boschma 2015*), which implies a change of economic structures (*Martin 2012*). While such changes could entail the change of industrial compositions as well as the intensity of labour flows between pairs of industries, it was not possible to take up on the task of exploring the dynamics of network robustness and its relation to resilience within the confines of this paper. Hence, our results apply to the resistance and recovery dimensions of resilience in particular, rather than to the dimensions of renewal and reorientation. That being said, without knowing more about heterogeneity in the network robustness of local inter-industry labour flows in a static sense, we cannot really discuss dynamic processes of change. Second, labour flows are only one instantiation of the interdependencies or forms of relatedness between different industries. With our data we could not assess the degree of supply chain relatedness between different local industries, which may lead to omitted variable bias. Considering both labour flows and supply chain connections in the same framework could however resolve the conundrum around related variety. That is, whether it allows for the emergence of novel combinations of local capabilities during crisis, or facilitates shock propagation between related segments of the local economy (*Boschma 2015, Martin & Sunley 2020*).

References

Albert, R., Jeong, H., & Barabási, A. L. (2000): Error and attack tolerance of complex networks. *Nature*, 406(6794): 378-382.

Andersson, L. F., Danley, T., Eriksson, R., & Henning, M. (2020): Workers' participation in regional economic change following establishment closure. *Small Business Economics*, 54(2): 589-604.

Balland, P. A., Rigby, D., & Boschma, R. (2015): The technological resilience of US cities. *Cambridge Journal of Regions, Economy and Society*, 8(2): 167-184.

Balland, P. A., Jara-Figueroa, C., Petralia, S. G., Steijn, M. P., Rigby, D. L., & Hidalgo, C. A. (2020): Complex economic activities concentrate in large cities. *Nature Human Behaviour*, 4(3): 248-254.

Barabási, A. L. (2016): *Network Science*. Cambridge: Cambridge University Press.

Boschma, R. (2015): Towards an evolutionary perspective on regional resilience. *Regional Studies*, 49(5): 733-751.

Boschma, R. (2017): Relatedness as driver of regional diversification: A research agenda. *Regional Studies*, 51(3): 351-364.

Boschma, R., & Martin, R. (2010): *The Handbook of Evolutionary Economic Geography*. Edward Elgar, Cheltenham – Northampton.

Boschma, R., Eriksson, R., & Lindgren, U. (2009): How does labour mobility affect the performance of plants? The importance of relatedness and geographical proximity. *Journal of Economic Geography*, 9(2): 169-190.

Boschma, R., Eriksson, R. H., & Lindgren, U. (2014): Labour market externalities and regional growth in Sweden: The importance of labour mobility between skill-related industries. *Regional Studies*, 48(10): 1669-1690.

Brakman, S., Garretsen, H., & van Marrewijk, C. (2015): Regional resilience across Europe: On urbanisation and the initial impact of the Great Recession. *Cambridge Journal of Regions, Economy and Society*, 8(2): 225-240.

Bristow, G., & Healy, A. (eds.) (2020a): *Handbook on Regional Economic Resilience.* Edward Elgar, Cheltenham – Northampton.

Bristow, G., & Healy, A. (2020b): Regional resilience: an agency perspective. In Bristow, G., and Healy, A. (eds.): *Handbook on Regional Economic Resilience.* Edward Elgar, Cheltenham – Northampton: 36-53.

Cohen, R., & Havlin, S. (2009): Percolation in Complex Networks. In Meyers, R. A. (ed.): *Encyclopedia of Complexity and Systems Science*. Springer, New York: 6495-6504.

Csáfordi, Z., Lőrincz, L., Lengyel, B., & Kiss, K. M. (2020): Productivity spillovers through labor flows: productivity gap, multinational experience and industry relatedness. *The Journal of Technology Transfer*, 45(1): 86-121.

Diodato, D., Neffke, F., & O'Clery, N. (2018): Why do industries coagglomerate? How Marshallian externalities differ by industry and have evolved over time. *Journal of Urban Economics*, 106: 1-26.

Doran, J., & Fingleton, B. (2018): US metropolitan area resilience: insights from dynamic spatial panel estimation. *Environment and Planning A: Economy and Space*, 50(1): 111-132.

European Commission (EC) (2017): *My Region, My Europe, Our Future. Seventh report on economic, social and territorial cohesion*. Publications Office of the European Union, Luxembourg.

Ellison, G., Glaeser, E. L., & Kerr, W. R. (2010): What causes industry agglomeration? Evidence from coagglomeration patterns. *American Economic Review*, 100(3): 1195-1213.

Eriksson, R. H., & Hane-Weijman, E. (2017): How do regional economies respond to crises? The geography of job creation and destruction in Sweden (1990–2010). *European Urban and Regional Studies*, 24(1): 87-103.

Eriksson, R. H., Henning, M., & Otto, A. (2016): Industrial and geographical mobility of workers during industry decline: The Swedish and German shipbuilding industries 1970–2000. *Geoforum*, 75: 87-98.

Eriksson, R. H., & Lengyel, B. (2019): Co-worker networks and agglomeration externalities. *Economic Geography*, 95(1): 65-89.

Eriksson, R., & Lindgren, U. (2009): Localized mobility clusters: impacts of labour market externalities on firm performance. *Journal of Economic Geography*, 9(1): 33-53.

Fitjar, R. D., & Rodríguez-Pose, A. (2017): Nothing is in the air. *Growth and Change*, 48(1): 22-39.

Fitjar, R. D., & Timmermans, B. (2017): Regional skill relatedness: towards a new measure of regional related diversification. *European Planning Studies*, 25(3): 516-538.

Frenken, K., Van Oort, F., & Verburg, T. (2007): Related variety, unrelated variety and regional economic growth. *Regional Studies*, 41(5): 685-697.

Fusillo, F., Consoli, D., & Quatraro, F. (2022): Resilience, Skill Endowment, and Diversity: Evidence from US Metropolitan Areas. *Economic Geography*, 98(2): 170-196.

Gianelle, C. (2014): Discovering the regional small world of labour mobility. evidence from linked employer–employee data. *Regional Studies*, 48(7): 1263-1278.

Glaeser, E. L. (2005): Reinventing Boston: 1630–2003. *Journal of Economic Geography*, 5(2): 119-153.

Glaeser, E. L., Kallal, H. D., Scheinkman, J. A., & Shleifer, A. (1992): Growth in cities. *Journal of Political Economy*, 100(6): 1126-1152.

Grillitsch, M., Martynovich, M., Fitjar, R. D., & Haus-Reve, S. (2021): The black box of regional growth. *Journal of Geographical Systems*, 23: 425-464.

Guerrero, O. A., & Axtell, R. L. (2013): Employment growth through labor flow networks. *PLOS One*, 8(5): e60808.

Hane-Weijman, E., Eriksson, R. H., & Henning, M. (2018): Returning to work: regional determinants of re-employment after major redundancies. *Regional Studies*, 52(6): 768-780.

Hane-Weijman, E., Eriksson, R. H., & Rigby, D. (2022): How do occupational relatedness and complexity condition employment dynamics in periods of growth and recession?. *Regional Studies*, 56(7): 1176-1189.

Hidalgo, C. A. (2021): Economic complexity theory and applications. *Nature Reviews Physics*, 3(2): 92-113.

Kitsos, T., Grabner, S. M., & Carrascal-Incera, A. (2023): Industrial embeddedness and regional economic resistance in Europe. *Economic Geography*, online first.

Lengyel, B., & Eriksson, R. H. (2017): Co-worker networks, labour mobility and productivity growth in regions. *Journal of Economic Geography*, 17(3): 635-660.

Martin, R. (2012): Regional economic resilience, hysteresis and recessionary shocks. *Journal of Economic Geography*, 12 (1): 1-32.

Martin, R., & Sunley, P. (2007): Complexity thinking and evolutionary economic geography. *Journal of Economic Geography*, 7(5): 573-601.

Martin, R., & Sunley, P. (2020): Regional economic resilience: evolution and evaluation. In Bristow, G., & Healy, A. (eds.). *Handbook on Regional Economic Resilience*. Edward Elgar, Cheltenham – Northampton: 10-35.

Martynovich, M., Hansen, T., & Lundquist, K-J. (2022): Can foundational economy save regions in crisis? *Journal of Economic Geography*, lbac027.

Massey, D. (1995): *Spatial Divisions of Labour. Social Structures and the Geography of Production (2nd Edition)*. Palgrave, London.

Moro, E., Frank, M. R., Pentland, A., Rutherford, A., Cebrian, M., & Rahwan, I. (2021): Universal resilience patterns in labor markets. *Nature Communications*, 12(1): 1-8.

Neffke, F., & Henning, M. (2013): Skill relatedness and firm diversification. *Strategic Management Journal*, 34(3): 297-316.

Neffke, F. M., Otto, A., & Weyh, A. (2017): Inter-industry labor flows. *Journal of Economic Behavior & Organization*, 142: 275-292.

Nyström, K. (2018): Regional resilience to displacements. *Regional Studies*, 52(1): 4-22.

O'Clery, N., & Kinsella, S. (2022): Modular structure in labour networks reveals skill basins. *Research Policy*, 51(5): 104486.

Pendall, R., Foster, K. A., & Cowell, M. (2010): Resilience and regions: building understanding of the metaphor. *Cambridge Journal of Regions, Economy and Society*, 3(1): 71-84.

Rocchetta, S., & Mina, A. (2019): Technological coherence and the adaptive resilience of regional economies. *Regional Studies*, 53 (10): 1421-1434.

Rocchetta, S., Mina, A., Lee, C., & Kogler, D. F. (2022): Technological knowledge spaces and the resilience of European regions. *Journal of Economic Geography*, 22(1): 27-51.

Sánchez-Moral, S., Vale, M., & Arellano, A. (2022): Skill-Relatedness and Regional Economic Development in Spain during the International Crisis and the Post-Crisis Period. *Papers in Regional Science*, 101(3): 573-602.

Shutters, S. T., Lobo, J., Muneepeerakul, R., Strumsky, D., Mellander, C., Brachert, M., Farinha, T., & Bettencourt, L. M. (2018): Urban occupational structures as information networks: The effect on network density of increasing number of occupations. *PLOS One*, 13(5): e0196915.

Simmie, J., and Martin, R. 2010. The economic resilience of regions: towards an evolutionary approach. *Cambridge Journal of Regions, Economy and Society*, 3(1): 27-43.

Solé, R. V., Rosas-Casals, M., Corominas-Murtra, B., & Valverde, S. (2008) Robustness of the European power grids under intentional attack. *Physical Review E*, 77(2): 026102.

Storper, M. (1997): *The Regional World: Territorial Development in a Global Economy*. Guilford Press, New York.

Tibshirani, R. (1996): Regression shrinkage and selection via the lasso. *Journal of the Royal Statistical Society: Series B (Methodological)*, 58(1): 267-288.

Tóth, G., Elekes, Z., Whittle, A., Lee, C., & Kogler, D. F. (2022). Technology network structure conditions the economic resilience of regions. *Economic Geography*, 98(4), 355-378.

Xiao, J., Boschma, R., & Andersson, M. (2018): Resilience in the European Union: The effect of the 2008 crisis on the ability of regions in Europe to develop new industrial specializations. *Industrial and Corporate Change*, 27(1): 15-47.

Zitnik, M., Feldman, M. W., & Leskovec, J. (2019): Evolution of resilience in protein interactomes across the tree of life. *Proceedings of the National Academy of Sciences*, 116 (10): 4426-4433.

Supplementary Information

SI 1. Descriptive statistics and correlation matrix

SI Table 1. Descriptive statistics and correlation matrix.

Variable	Obs.	Mean	Std. Dev.	Minimum	Maximum
(1) $\log_{10} REGEMP_{2007}$	72	4.196	0.683	3.004	6.047
(2) $HUMCAP_{2007}$	72	0.246	0.055	0.157	0.412
(3) $POPDENS_{2007}$	72	22.385	22.385	0.241	145.413
(4) Ω^R	72	0.414	0.022	0.361	0.451
(5) Ω^T	72	0.287	0.064	0.171	0.432
(6) $RELVAR_{2007}$	72	2.701	0.394	1.742	3.327
(7) $UNRELVAR_{2007}$	72	3.218	0.175	2.675	3.507
(8) $THEIL_{2007}$	72	3.396	5.945	-0.940	29.513
(9) DIV_{2007}	72	7.738	1.499	4.036	10.566
(10) RSR_{2007}	72	13.206	3.875	6.019	20.058
(11) ECI_{2007}	72	0.131	0.145	0.000	1.000

Correlation matrix

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
(1)	1.000										
(2)	0.806	1.000									
(3)	0.775	0.640	1.000								
(4)	0.956	0.760	0.631	1.000							
(5)	0.950	0.809	0.703	0.940	1.000						
(6)	0.881	0.582	0.608	0.874	0.814	1.000					
(7)	0.219	0.482	0.163	0.243	0.324	-0.046	1.000				
(8)	-0.451	-0.251	-0.345	-0.404	-0.391	-0.592	0.303	1.000			
(9)	0.198	0.464	0.172	0.210	0.303	-0.081	0.982	0.321	1.000		
(10)	0.972	0.761	0.688	0.963	0.928	0.924	0.186	-0.457	0.158	1.000	
(11)	0.683	0.683	0.814	0.558	0.646	0.424	0.356	-0.137	0.386	0.566	1.000

SI 2. LASSO and LASSO selection

Hastie et al. (2019) discuss how to use LASSO for model selection and for inferential questions even with small samples. For linear models, LASSO solves a similar optimization problem as the Least Square estimator does, except it includes a penalization parameter:

$$\hat{\beta} = \operatorname{argmin}\left\{\frac{1}{2N}\sum_{i=1}^{n}(y_i - x_i\beta') + \lambda\sum_{j=1}^{p}\omega_j|\beta_j|\right\} \quad (1)$$

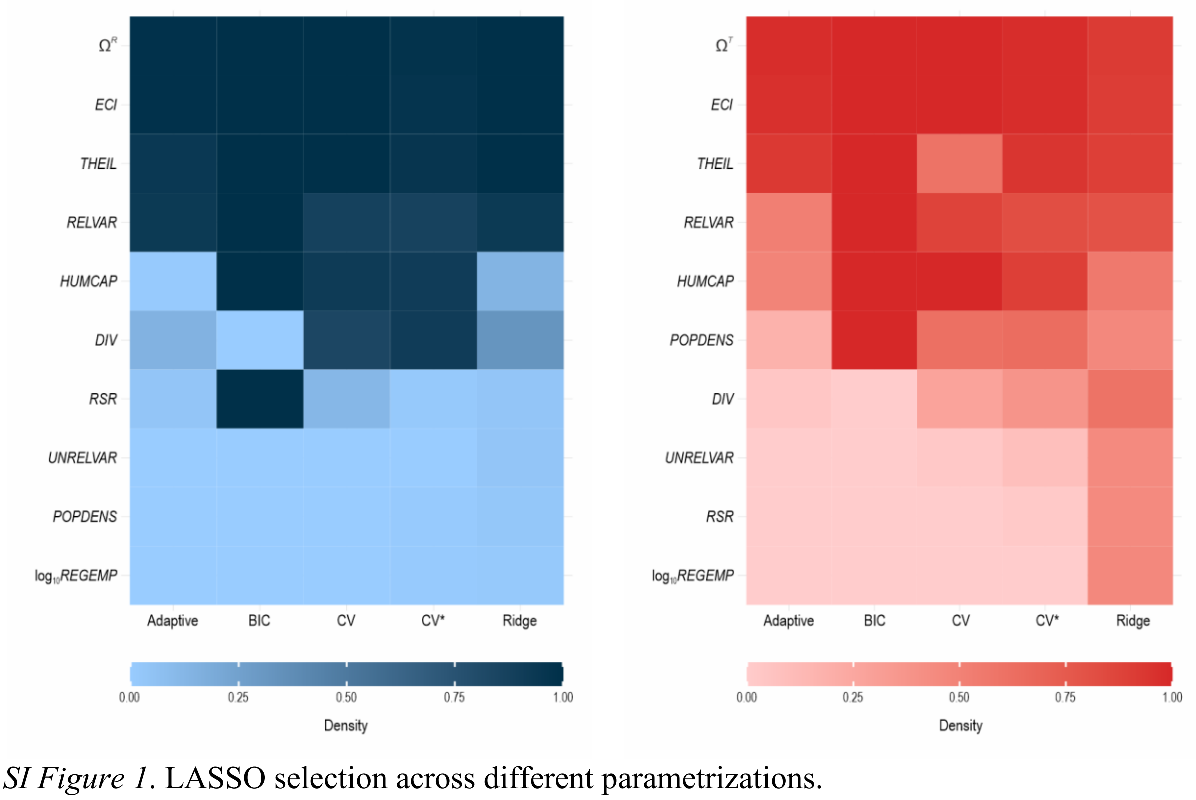
, where the first term refers to the least-square optimization process to minimize the squared residuals and the second term introduces the penalty term. In the penalty term $\lambda \in \{0, \infty)$ is the LASSO penalization parameter and ω_j is a parameter-level weight.

When λ takes the value of zero the estimation reduces back the Least Square optimization. With increasing values of λ the degree of all the estimated coefficients is diminishing towards zero. The diminishing arises because the penalty term adds up from the absolute values of β_j. At given penalty parameters, the optimal solution for some of the estimated coefficients is zero. When we use LASSO for variable selection, the covariates with an estimated coefficient of zero can be excluded from the model. This process solves the high dimensionality of the model: in other words, it keeps only the covariates that have a reliable estimate despite collinearity and the relative smallness of the sample.

In the main model we used adaptive LASSO, which is a modification of the standard LASSO that aims to improve its performance when the number of predictor variables is large. The idea behind adaptive LASSO is to introduce a data-driven weighting scheme for the penalty term that gives more weight to important predictors and less weight to less important ones, which leads to consistent variable selection. As sensitivity check, we applied other frequently used other methods to ensure the consistency our estimation. Since the number of excluded covariates could be dependent on the value of λ, we used different versions of cross-validation (CV) to determine the optimal value of λ (*Chetverikov et al. 2021*). Cross-validation simulates the process of using split samples to optimize the most efficient out-of-sample predicators. CV method identifies the optimal value of λ that minimizes the out-of-sample mean squared error of the predictions and maximizes the predictive power of the model.

To reduce bias from overfitting highly correlating variables on low sample size, we run LASSO regressions to identify the set of variables with non-zero coefficients (*Hastie et al. 2009*). Then fit an unrestricted OLS model on the selected set of features. The idea is to run the LASSO selection multiple times in tandem and use cross-validation to refine the group of predictors to prevent over-fitting. Then the OLS we run with the selected set of variables should be free from overfitting bias (see *Table 2* and *3*). However, the variable selection depends on how we select the value of λ from *Equation (1)*.

(A) **(B)**



SI Figure 1. LASSO selection across different parametrizations.
Note: blue corresponds to random and red corresponds to targeted elimination.

The most common selection method is LASSO with λ selected by cross-validation (CV). With this method, we set a CV function $f(\lambda)$ with which we want to minimize the estimated out-of-sample prediction error. In this case, the optimal λ minimizes the CV function. For more details on $f(\lambda)$ see *Obuchi & Kabashima (2016)*. With CV, the number of covariates tends to vary on a wide interval. Therefore, in the following specification (CV*), we set the minimum number of selected covariates to six. With CV*, LASSO selects the first six variables that minimize the out-of-sample error. Another method to reduce the number of variables is Adaptive LASSO. The Adaptive method aims to find parsimonious models that might reflect the true model better. Adaptive LASSO is also using CV solutions, but it is a more conservative method since it selects a model that has fewer covariates. For another robustness check, we repeated the same exercise, but we picked the λ that has the minimum Bayes Information Criterion (BIC). Finally, as a complementary method, we used Ridge regression. In Ridge regression, the penalization parameter from *Equation (1)* is altered by changing $\lambda \sum_{j=1}^{p} \omega_j |\beta_j|$ to the square of the magnitude of the coefficients, such $\lambda \sum_{j=1}^{p} \omega_j \beta_j^2$. Ridge regression helps to shrink the coefficients but rarely excludes variables from the model.

SI 3. Defining the variables of local industrial structure

In this subsection we provide the formal definition of variables that describe the local industrial structure, and that we use in the LASSO selection model. These variables are calculated for 2007.

First, the *related variety* of industries within a region r ($RELVAR_r$) is defined through entropy decomposition (*e.g. Frenken et al. 2007*) as the weighted average entropy of employment within 1-digit industry groups. If every 3-digit industry i falls under a 1-digit industry group S_g, where $g = 1, \dots, G$, then related variety is calculated as

$$RELVAR_r = \sum_{g=1}^{G} P_g H_g \tag{2}$$

where P_g is the aggregation of the 3-digit employment shares:

$$P_g = \sum_{i e S_g} p_i \tag{3}$$

The entropy within each 1-digit industry group S_g is H_g:

$$H_g = \sum_{ieS_g} \frac{p_i}{P_g} \log_2 \left(\frac{1}{p_i/P_g} \right) \quad (4)$$

Unrelated variety ($UNRELVAR_r$) is measured as the entropy of the distribution of employment across 1-digit industries in a region:

$$UNRELVAR_r = \sum_{g=1}^{G} P_g \log_2 \left(\frac{1}{P_g} \right) \quad (5)$$

Second, we use the *regional skill relatedness* (RSR_r) measure introduced by *Fitjar & Timmermans (2017)*. Essentially, this measure takes a skill-relatedness network defined from inter-industry labour flows observed across the national economy, and then calculates the average relatedness of industries within a region, while also considering the size of these industries in terms of employment. The measure can be considered an improved related variety measure in that it considers *ex post* relatedness, as opposed to deriving it from a classification scheme. It is defined formally as

$$RSR_r = \frac{\left(\sum_{i=1}^{N} \left(\frac{\sum_j SR_{ij,r}}{2} \right) \sqrt{q_{i,r}} \right) / N_r}{\left(\sum_{i=1}^{N} \sqrt{q_{i,r}} \right) / N_r} \quad (6)$$

Here, $SR_{ij,r}$is the inter-industry labour flow measure, between 3-digit industries i and $j \neq i$ that is present in region r, as described in *Subsection 3.2.*, but derived from aggregate labour flows at the national level (hence following a revealed skill-relatedness approach). $q_{i,r}$ is the employment share of a 3-digit industry i from the total employment in region r, while N_r is the number of 3-digit industries present in a region. A higher value of this indicator signals a higher employment-weighted average skill-relatedness within a local labour market, hence higher worker redeployment potential between industries. While this measure is akin to our network robustness measure, from a structural perspective it considers only the immediate (1-step) neighborhood of each industry, while our measure captures a more global structural feature of each labour flow network, at the local level.

Third, we follow *Grillitsch et al. (2021)*'s approach and formulation in considering two additional measures of industry mix and agglomeration. The first is the *absolute diversity* (DIV_r) of the regional employment mix using a reverse Herfindahl-Hirschman index:

$$DIV_r = \frac{1}{\sum_{g=1}^{G} Q_{g,r}^2} \tag{7}$$

Here, $Q_{g,r}$ represents the employment share of 1-digit industry g ($g = 1, \dots, G$) in the employment portfolio of region r. A higher value of absolute diversity indicates that regional employment is less concentrated across industries.

The second variable is a measure of *relative regional specialisation* ($THEIL_r$). Building on the Theil Index, this measure aggregates industry-region level specialisations (measured by a location quotient) to the regional level. Formally:

$$THEIL_r = \sum_{g=1}^{G} \frac{Q_{g,r}}{Q_g} \ln\left(\frac{Q_{g,r}}{Q_g}\right) \tag{8}$$

Here, $Q_{g,r}$ is again the employment share of 1-digit industry g ($g = 1, \dots, G$) in the employment portfolio of region r, while Q_g is the employment share of the same industry in the national employment. A higher value of relative regional specialisation would indicate that a region is specialised in its industry structure *compared to other regions* in the Swedish economy.

Finally, we include *economic complexity* (ECI_r) as a quality of the local capability base within the regions under analysis. It is widely established in the literature that complexity is a strong predictor of long term economic growth (*e.g. Hidalgo & Hausmann 2009, Rigby et al. 2022*). Here, we use the so-called Method of Reflections introduced by *Hidalgo & Hausmann (2009)*. That is, we take a matrix with regions in its rows and industries in its columns ($M_{r,i}$), where each cell of the matrix shows whether region r has a location quotient of employment above 1 in industry i. The next step is to calculate the diversity of regions and the ubiquity of industries:

$$DIVERSITY_r = K_{r,0} = \sum_i M_{r,i} \tag{9}$$

$$UBIQUITY_i = K_{i,0} = \sum_r M_{r,i} \tag{10}$$

The economic complexity of regions (and industries) can then be obtained by sequentially combining these two measures in the following equations over n iterations:

$$ECI_r = K_{r,n} = \frac{1}{K_{r,0}} \sum_i M_{r,i} K_{i,n-1} \tag{11}$$

$$ICI_i = K_{i,n} = \frac{1}{K_{i,0}} \sum_r M_{r,i}\, K_{r,n-1} \tag{12}$$

The final value of ECI_r is normalized between 0 and 1, essentially creating a ranking between regions based on their industrial structure (*Mealy et al. 2019*), where a higher value corresponds to a more complex economic structure. For a more detailed description on the Method of Reflections, we refer the reader to *Hidalgo & Hausmann (2009)*, or to *Balland & Rigby (2017)* for an application in the context of technological complexity within regions.

SI 4. Robustness checks

SI Table 2. Regression results with combined removal.

	Dependent variable: employment change 2007-2012				
	(1) OLS (baseline)	**(2)** OLS	**(3)** LASSO inference (adaptive)	**(4)** LASSO selection	**(6)** OLS with LASSO selection
$\log_{10} REGEMP_{2007}$	-0.041 (0.030)	0.029 (0.066)	0.006 (0.069)		
$POPDENS_{2007}$	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)		
$HUMCAP_{2007}$	0.294* (0.151)	0.067 (0.169)	0.073 (0.156)		
Ω^H_{2007}	0.614 (0.375)	0.499 (0.368)	0.589 (0.407)	X	0.387*** (0.127)
$RELVAR_{2007}$		-0.034 (0.042)	-0.040 (0.041)		
$UNRELVAR_{2007}$		-0.119 (0.145)	-0.114 (0.156)		
$THEIL_{2007}$		0.002* (0.001)	0.002 (0.002)	X	0.003** (0.001)
DIV_{2007}		0.014 (0.017)	0.011 (0.019)		
RSR_{2007}		-0.003 (0.010)	0.001 (0.010)		
ECI_{2007}		0.075 (0.073)	0.079 (0.066)	X	0.096** (0.038)
Constant	0.858*** (0.045)	1.061*** (0.352)			0.821*** (0.042)
# Region	72	72	72	72	72
R^2	0.258	0.423			0.384
Adjusted R^2	0.213	0.328			0.357
Mean VIF	9.43	29.57			1.61
F-Statistic	5.81***	4.47***			14.14***

Note: standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

SI Table 3. Regression results excluding metro regions.

	Dependent variable: employment change 2007-2012			
	(1) OLS (baseline)	**(2)** OLS (baseline)	**(3)** OLS with LASSO selection	**(4)** OLS with LASSO selection
$\log_{10} REGEMP_{2007}$	-0.079* (0.037)	-0.014 (0.027)		
$POPDENS_{2007}$	0.000 (0.000)	-0.000 (0.000)		
$HUMCAP_{2007}$	0.268 (0.145)	0.208 (0.157)		
Ω^R_{2007}	2.635** (0.910)		1.713*** (0.481)	
Ω^T_{2007}		0.394 (0.251)		0.246** (0.111)
$RELVAR_{2007}$			-0.066** (0.026)	
$THEIL_{2007}$			0.001* (0.000)	0.002*** (0.000)
ECI_{2007}			0.095 (0.026)	0.136 (0.081)
Constant	0.155 (0.241)	0.882*** (0.352)	0.428*** (0.141)	0.879*** (0.028)
# Region	69	69	69	69
R^2	0.259	0.193	0.367	0.290
Adjusted R^2	0.213	0.143	0.327	0.258
Mean VIF	11.67	6.47	3.77	1.74
F-Statistic	5.62***	3.85**	9.29***	9.97***

Note: standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

SI Table 4. Regression results for alternative period.

	Dependent variable: employment change 2007-2009			
	(1) OLS (baseline)	**(2)** OLS (baseline)	**(3)** OLS with LASSO selection	**(4)** OLS with LASSO selection
$\log_{10} REGEMP_{2007}$	-0.037 (0.026)	-0.002 (0.018)		
$POPDENS_{2007}$	0.000 (0.000)	0.000 (0.000)		
$HUMCAP_{2007}$	0.161 (0.101)	0.130 (0.107)		
Ω^{R}_{2007}	1.235* (0.626)		1.329*** (0.302)	
Ω^{T}_{2007}		0.149 (0.175)		0.217*** (0.068)
$RELVAR_{2007}$			-0.048*** (0.018)	
$THEIL_{2007}$			0.000 (0.000)	0.001*** (0.000)
ECI_{2007}			0.044* (0.024)	0.045 (0.028)
Constant	0.567*** (0.163)	0.900*** (0.035)	0.538*** (0.087)	0.892*** (0.018)
# Region	72	72	72	72
R^2	0.264	0.230	0.429	0.336
Adjusted R^2	0.220	0.184	0.395	0.307
Mean VIF	13.84	7.65	3.69	1.67
F-Statistic	6.02***	5.00**	12.57***	11.48***

Note: standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

SI References

Balland, P. A., & Rigby, D. (2017): The geography of complex knowledge. *Economic Geography*, 93(1): 1-23.

Chetverikov, D., Liao, Z., & Chernozhukov, V. (2021): On cross-validated lasso in high dimensions. *The Annals of Statistics*, 49(3): 1300-1317.

Fitjar, R. D., & Timmermans, B. (2017): Regional skill relatedness: towards a new measure of regional related diversification. *European Planning Studies*, 25(3): 516-538.

Frenken, K., Van Oort, F., & Verburg, T. (2007): Related variety, unrelated variety and regional economic growth. *Regional Studies*, 41(5): 685-697.

Grillitsch, M., Martynovich, M., Fitjar, R. D., & Haus-Reve, S. (2021): The black box of regional growth. *Journal of Geographical Systems*, 23: 425-464.

Hastie, T., Tibshirani, R., Friedman, J. H., & Friedman, J. H. (2009): *The elements of statistical learning: data mining, inference, and prediction (Vol. 2)*. Springer, New York.

Hidalgo, C. A., & Hausmann, R. (2009): The building blocks of economic complexity. *Proceedings of the National Academy of Sciences*, 106(26): 10570-10575.

Mealy, P., Farmer, J. D., & Teytelboym, A. (2019): Interpreting economic complexity. *Science Advances*, 5(1): eaau1705.

Obuchi, T., & Kabashima, Y. (2016): Cross validation in LASSO and its acceleration. *Journal of Statistical Mechanics: Theory and Experiment*, 2016(5): 053304.

Rigby, D. L., Roesler, C., Kogler, D., Boschma, R., & Balland, P. A. (2022): Do EU regions benefit from Smart Specialisation principles? *Regional Studies*, 56(12): 2058-2073.