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Regional resilience and the network structure of inter-industry labour flows

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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 financial 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.

JEL codes: J21, L14, R11, R23
Keywords: local capability base; inter-industry labour flows; skill-relatedness; network robustness; regional economic resilience; regional employment

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A regionális rugalmasság és az iparágak közötti munkaerőáramlás hálózati szerkezete

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ÖSSZEFOGLALÓ

Ez a tanulmány azt vizsgálja, hogy a helyi iparágak közötti munkaerő-áramlás hálózati szerkezete hogyan kapcsolódik a regionális gazdasági rugalmassághoz 72 svédországi lokális munkaerőpiacon. A hálózattudomány legújabb eredményeire támaszkodva stresszteszteljük ezeket a hálózatokat a csomópontjaik szekvenciális megszüntetésével. A 2008-as pénzügyi válsággal összefüggésben a LASSO-szelekcióval végzett regresszióelemzés azt mutatja, hogy a munkaerőáramlási hálózatok robusztussága a válság alatti foglalkoztatási változások egyik szignifikáns prediktora. Ezek az eredmények azt mutatják be, hogy a regionális gazdaságok, mint önszerveződő komplex rendszerek hogyan eredményezik a rugalmasabb vagy kevésbé rugalmas régiós gazdaságok kialakulását.

JEL: J21, L14, R11, R23

Kulcsszavak: helyi képességbázis; iparágak közötti munkaerő-áramlás; képesség hasonlóság; hálózati robusztusság; regionális gazdasági ellenálló képesség; regionális foglalkoztatás

Regional resilience and the network structure of inter-industry labour flows

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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 financial 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.

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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 their long-term capacity for growth, as a region's level of success in coping with one crisis conditions its ability to deal with subsequent ones (Simmie & Martin, 2010). Consequently, the differential growth impact of a crisis 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 the catching up of member states with less developed economies (EC, 2017). Subsequent crises, like the pandemic and rising energy prices, also had distinct and somewhat different regional socio-economic effects across seemingly similar regions (e.g., Gray et al., 2023; Garcia-Muros et al., 2023).

Knowing more about the capacity of different regions to both resist and recover from economic turmoil is therefore high on 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., Di Caro, 2017; Eriksson & Hane-Weijman, 2017; Martin & Sunley, 2020; Fusillo et al., 2022), previous studies seldom transcend the specialisation-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 regarded as (knowledge) networks in which nodes represent specific economic activities, while ties represent the degree of shared productive capabilities or the intensity of exchange between them (Boschma, 2015).

However, our understanding of 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 their 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 to economic outcomes during crisis. Other networks than those of technologies are underrepresented in the literature, however, despite the fact that crisis-induced employment effects tend to be more persistent than output effects (Martin, 2012). The few notable exceptions that go 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 nationwide definitions of relatedness, both of which may cause an urban bias in how capabilities are defined and thus how resilience is interpreted. This is not a trivial bias, as non-metro regions are particularly important for better understanding regional resilience. For example, medium-sized regions had the highest resistance and fastest recovery in Italy in the context of the 2008 financial crisis (Faggian et al., 2018), while smaller regions have been consistently struck harder and have struggled more to develop new growth paths across multiple crises in Sweden since the 1990s (Eriksson & Hane-Weijman, 2017). Consequently, there is a need of comprehensive analyses of inter-industry networks in local labour markets across the spatial hierarchy 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 to 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 economic crisis of 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). A discussion of implications, limitations and open questions for future research concludes the paper (Section 5).

We thereby contribute 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 even between regions of similar size. Contrasting theory-driven regression models with data-driven LASSO inference and selection approaches, we show that labour flow network 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 to the elimination of nodes and links from the network representation of their economic structure (e.g., Boschma, 2015). Thereby, the paper also connects these bodies of literature more tightly to 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 specialisation regardless of whether, for instance, industries, occupations or technology and scientific domains are considered. Additionally, the locations of economic activities are not independent of each other. Instead, some pairs of activities are more likely than others to be found at the same place. Such a 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 has increased over the last century, especially for service sectors (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 that workers be able to access, interpret and apply such knowledge. Knowledge is then shared through interaction and mobility. Indeed, firms that are inter-linked by localised 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 have 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 simply 'in the air' even in industry clusters (Fitjar & Rodríguez-Pose, 2017) but rather requires access through being part of such localised 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 to regional growth. Instead, inflows of workers with skills 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 and diversification (Diodato et al., 2018), as well as the productivity and employment growth of regions, as compared to highly diverse flows (Boschma et al., 2014). Hence, labour flows represent an underlying structuring aspect of agglomeration. As 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 than mobility between them (O'Clery & Kinsella, 2022). This property has been extensively built upon in analyses of 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 literature above 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 (or less) 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, here robustness means the rate at which the underlying network of a complex system is fragmented into too many disconnected components (e.g., 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 of our existing knowledge of local labour market structures, but is particularly important in understanding regional economic resilience. Considerable effort has recently been devoted, in both policy and academia, to better understanding 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 other regions of similar size and specialisation (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 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, which 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. Empirical evidence indicates that a diversified industrial structure characterises the most resilient regions, for instance in the US (Fusillo et al., 2022) or Italy (Di Caro, 2017).

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. Agricultural and traditional manufacturing specialisations exhibit substantial heterogeneity in contributing to resistance and recovery (Faggian et al., 2018). Moreover, evidence from Sweden suggests that regional employment in sectors associated with the foundational economy were more resilient to 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., 2023).

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. Evidence from European regions in the context of the 2008 financial crisis supports this idea, as the related variety of industries was beneficial to maintaining and increasing dynamism in developing new growth paths both during and after crisis (Xiao et al., 2018). 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), especially in the case of a vertically integrated industry portfolio (Cainelli et al., 2019). 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), is also considered. On the other hand, potentials for redeployment to related industries are particularly important in cases of involuntary displacement of workers following major plant closures (Hane-Weijman et al., 2018; Nyström, 2018), and as demand shocks unfold (Diodato & Weterings, 2015). Hence, tension remains in the literature regarding how relatedness within the local economy shapes regional resilience.

Furthermore, while regional economies can be regarded as webs of specialised 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, p. 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.*'

While this approach suggested by Boschma (2015) has in fact been extensively researched in network science in the context of various biological, infrastructural and social networks (Barabási, 2016), 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, entries and structural change to major economic recessions and natural disasters (Martin & Sunley, 2007) – there are clear bridges between the two strands of literature. Expanding on the argument by Shutters et al. (2018), 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 that is 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 the 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 their differential capacity 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 to 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). Far fewer studies have 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 negative association with peak unemployment during the 2008 recession (Moro et al., 2021). Sanchez-Moral et al. (2022) also found that Spanish regions with a higher density of skill-related industries both resisted and adapted to the 2008 recession better than less cohesive regions did. 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 influences 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 tends to represent particular industries due to the heterogeneity in the propensity to patent. Second, and related to the first, many of these findings specifically concern large urban areas, typically using nationwide projections of relatedness on the regional economies, while smaller regions tend to be neglected despite being more 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 in this paper. Based on the arguments above, our expectation is that the robustness of local labour flow networks can predict 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. The sudden demand shock resulting from the financial crisis hit some firms and regions hard, but in different ways. In urban regions the financial sector was put under pressure, while outside the metropolitan regions the crisis especially hit in regions where lead firms (e.g., automotives) were heavily reliant on the US market. Thus, while national unemployment peaked at around 9% (similar to during the pandemic), the regional effects were highly asymmetrical (Hörnström, 2011).

3. Research design

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 in the Swedish economy between 2002 and 2012 on an annual basis. Workers are linked to one of 264 industries, corresponding to three-digit industry codes in the NACE Rev. 2 classification system, and one of 72 functional labour market regions (FA regions) through the characteristics of their workplaces. These regions were identified by the Swedish Agency for Economic and Regional Growth (2011) by aggregating municipalities based on observed commuting flows around an urban core and consistent economic structures. They represent local labour markets where people reside and work (ca. 95% of the workforce work and live in the same FA), hence mitigating the risk of spatial dependence from labour flows across geographically proximate labour markets (e.g., Boschma et al., 2014; Hane-Weijman et al., 2022).

Building on this dataset, we first construct region-specific labour flow networks to capture the local specificities of labour reallocation between industries. We then assess the robustness of these networks against the sequential elimination of nodes (i.e., industries), employing a novel method adapted from network science. Finally, we validate the relationship between labour flow network robustness and regional resilience through regression analysis.

3.1. 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 normalised 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 specialisation, as measured by revealed comparative advantage (location quotient greater than 1), and normalised 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 basis of industries that are 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 market structures that are captured by them.

Motivated by these considerations, we opt to construct normalised 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 the crisis (see SI Figure 2). More specifically, two industries are considered connected by labour flows locally, if the 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 three-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 is common in research using skill-relatedness (e.g., Neffke et al., 2017), we first consider the average of SR_{ij} and SR_{ji} to obtain 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; thus, we normalise the measure to have its range between -1 and +1[1]. Hence, in this framework a normalised skill-relatedness of above 0 corresponds to an above-expected labour flow, on which the network representations of local labour markets are based.

3.2. Network robustness

We then assess the topological robustness of these networks to 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 normalised skill-relatedness is $\widetilde{SR}_{ij} = \frac{SR_{ij}-1}{SR_{ij}+1}$.

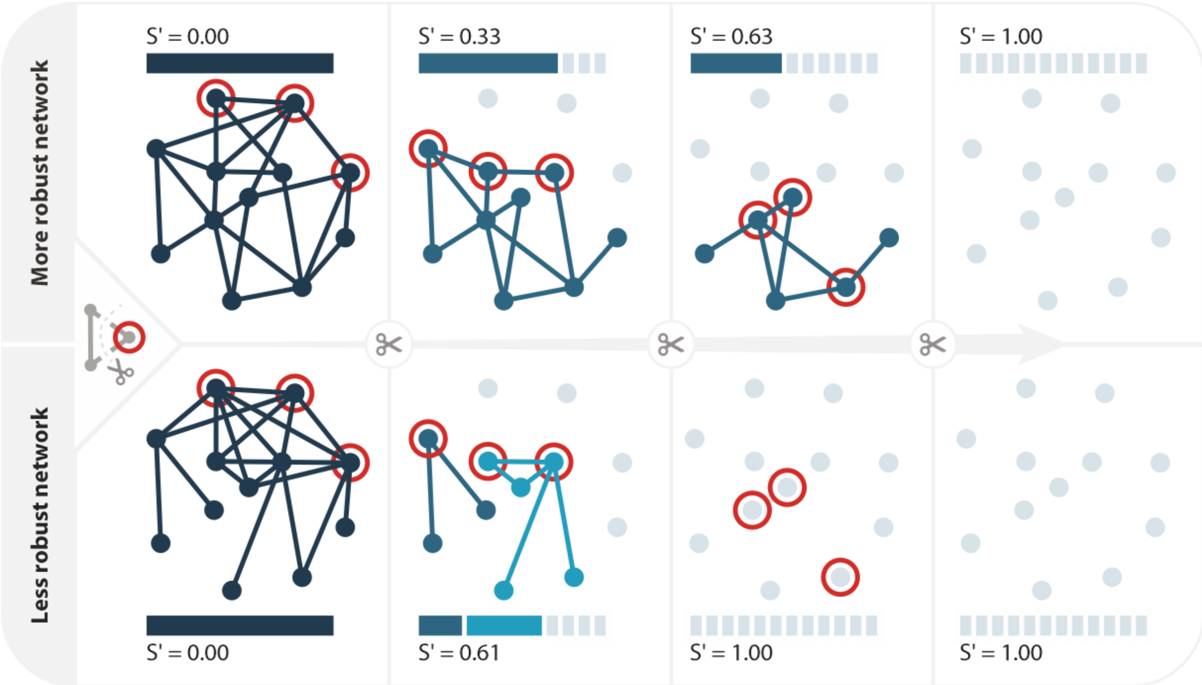

Figure 1. Network components and the robustness of local labour flow networks.

Note: S' indicates the normalised 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 were 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. We then calculate the Shannon entropy of node distribution across the isolated components of $G_i^f(C_k)$:

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

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 differently sized industry portfolios, we scale the Shannon entropy with the log number of industries present in the region:

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

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 1 minus the area under this curve:

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

The measure ranges from 0 to 1, where a higher value refers 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 is 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 3).

Figure 2 presents descriptive information on network robustness based on random and targeted elimination. Subfigures (A) and (B) show that the normalised 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 more slowly.

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 latter case. 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.

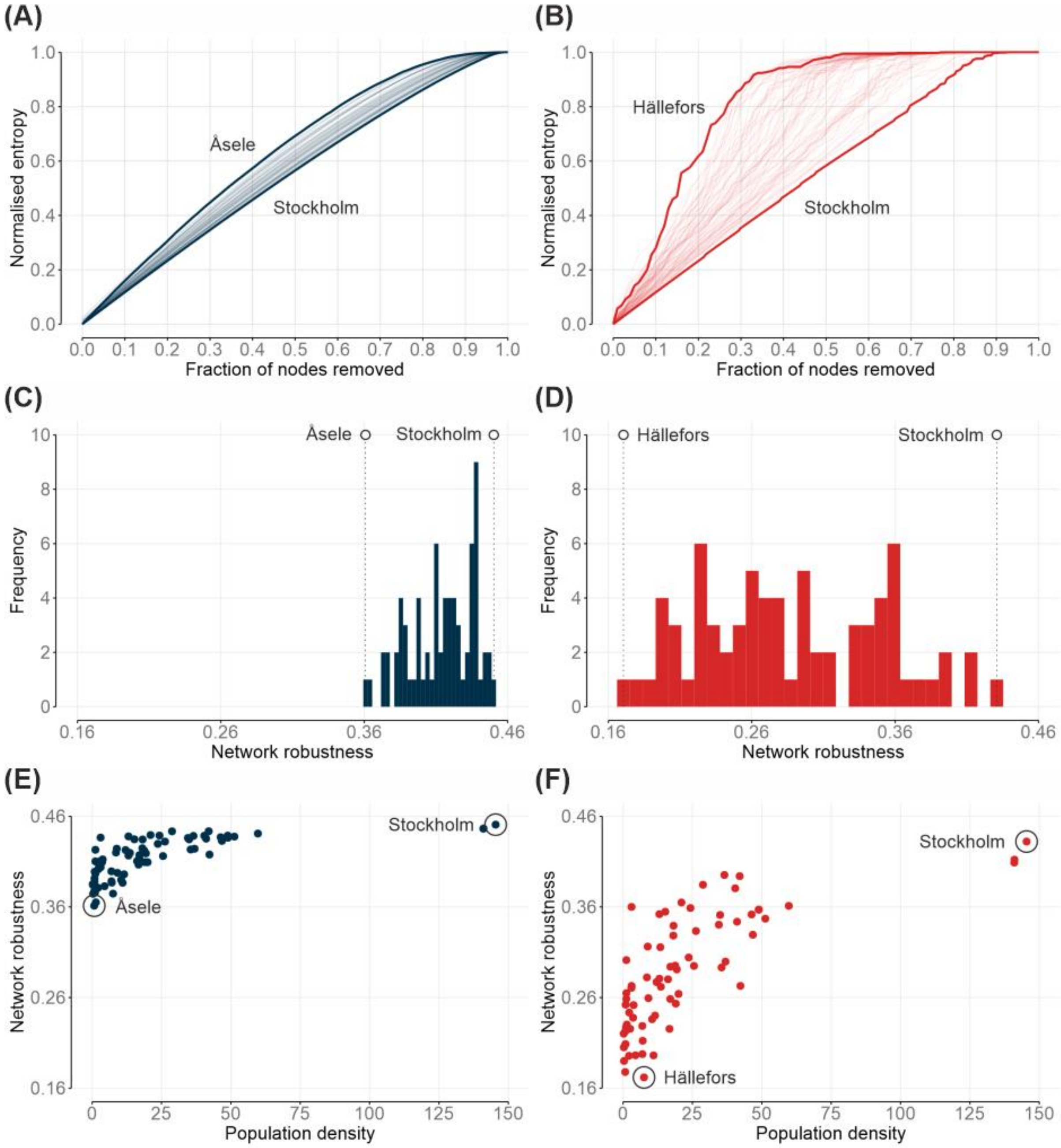

Figure 2. Descriptive information on the robustness of local labour flow networks.

Note: Blue represents results on random elimination, red on targeted elimination.

3.3. 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., 2023), 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 by 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 network robustness Ω of an industry network G_i to *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 who have a tertiary education, as higher-educated workers tend to have a more advantageous labour market status both 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 a skilled workforce (Glaeser 2005). Third, various additional measures of local industrial structure have been established in the literature that may be conducive to 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 4). The pairwise correlations of these variables are often high (see SI Table 1) and, together with the relatively high VIF values (see 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 a 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 3). As LASSO selection needs multiple runs and offers several parametrisation 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 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 (apart from the mining region of Kiruna) and in central Sweden that have the lowest robustness. This general robustness pattern resembles the regional effects of previous crises in recent decades. The metro regions and large regional centres tend to be more resilient to general crises, while more sector-specific shocks (e.g., the ICT crisis in the early 2000s) mainly entail an urban crisis (Eriksson & Hane-Weijman, 2017). Thus, the robustness derived from 2002-2007 data seems to reflect a more long-lasting regional capacity to manage crises. 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 elimination, indicating a more specialised and coherent industry structure.

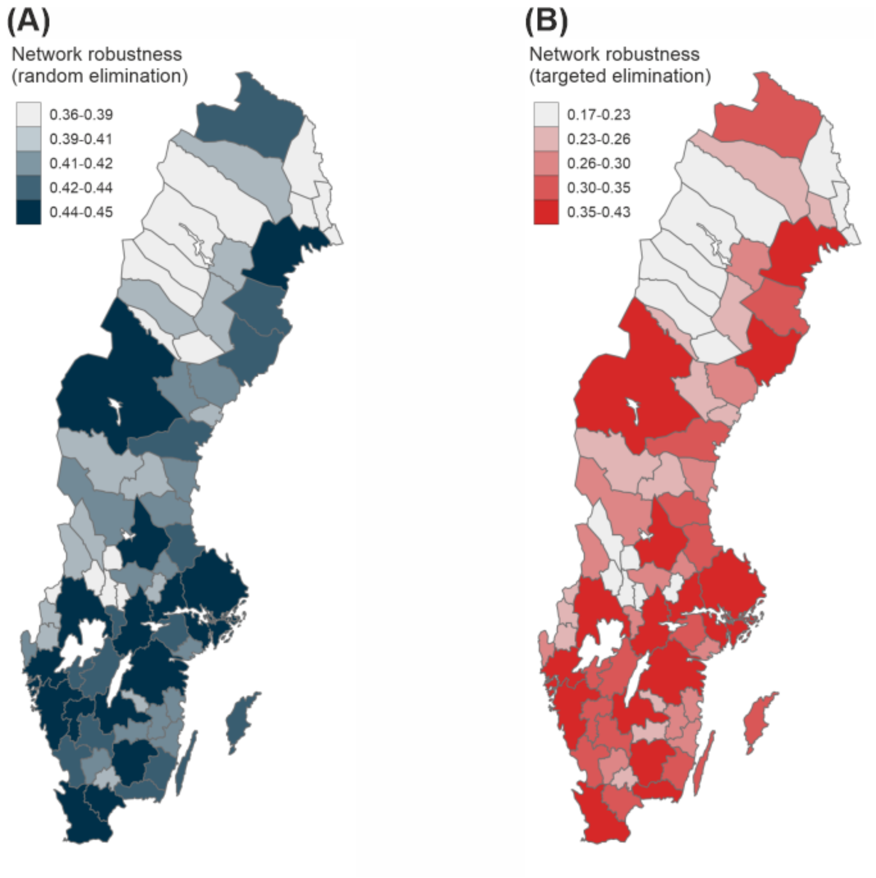

Figure 3. Mapping the robustness of local inter-industry labour flow networks across Sweden. Note: Based on labour flows aggregated across 2002-2007.

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

Tables 1 and 2 present the results of our regression analyses, including robustness to random and targeted elimination of industries (Ω^R and Ω^T), respectively. Model 1 in both tables represents a theory-driven employment growth model whereby coefficients are obtained using an OLS estimator. Model 2 extends this basic model by adding multiple variables on local industrial structure that are also considered in the resilience literature. As 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 Tables 1 and 2). This potential problem of multicollinearity further increases once we include alternative measures that capture aspects of local industrial portfolios. To mitigate this problem, the next set of models report the results of the LASSO inference that identifies the most stable predictors of the outcome variable in the case of a small number of observations, compared with a larger number of potentially collinear predictors. Model 3 in Tables 1 and 2 reports the coefficients obtained from LASSO inference, while Model 4 indicates the variables that were selected by the LASSO inference as the main predictors of employment change. 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.

Control variables in Model 1 in both tables show the expected signs, but significant coefficients are found mainly for the model with network robustness based on random elimination. The stepwise introduction of variables shows that these signs are consistent despite the likely presence of multicollinearity in the case of multivariate analysis (see SI Table 2). The results of the LASSO selection indicate that the robustness of local labour flow networks is the most consistently present predictor among all the variables considered (SI Figure 1). In the OLS models with LASSO-selected variables, we find that the robustness of the local labour flow network to both random and targeted removal of industries has a significant positive association with employment change. Hence, 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, disturbances in a particular industry will likely leave others that are still reliant on similar worker capabilities operational. Additionally, workers belonging to industries that are more isolated in the local labour flow network have fewer redeployment options in the case of job loss in the wake of the crisis. Thus, our results complement previous findings indicating that the availability of skill-related alternatives makes the re-employment of workers after plant closures easier (e.g., Diodato & Weterings, 2015; Morkuté et al., 2017; Hane-Weijman et al., 2018), by taking a more aggregate and systemic perspective.

Table 1. 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	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; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

Importantly, both interpretations above depend on the structure of labour flow networks among local industries. In this way our findings are in line with those of recent contributions regarding local network structures and resilience (Moro et al., 2021; Tóth et al., 2022), while expanding on these analyses by considering the regional industrial structure in particular, as well as by moving beyond the analysis of metropolitan regions.

Table 2. 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	0.046	0.026		
	(0.026)	(0.066)	(0.072)		
$POPDENS_{2007}$	0.000	-0.000	-0.000		
	(0.000)	(0.000)	(0.000)		
$HUMCAP_{2007}$	0.290*	0.064	0.067		
	(0.154)	(0.170)	(0.161)		
Ω^T	0.334	0.216	0.267	X	0.280***
	(0.252)	(0.249)	(0.283)		(0.097)
$RELVAR_{2007}$		-0.031	-0.036		
		(0.042)	(0.042)		
$UNRELVAR_{2007}$		-0.111	-0.105		
		(0.146)	(0.153)		
$THEIL_{2007}$		0.002*	0.002	X	0.003***
		(0.001)	(0.002)		(0.001)
DIV_{2007}		0.014	0.011		
		(0.018)	(0.019)		
RSR_{2007}		-0.003	-0.000		
		(0.010)	(0.020)		
ECI_{2007}		0.071	0.074	X	0.091**
		(0.073)	(0.068)		(0.040)
Constant	0.917***	1.075***			0.874***
	(0.051)	(0.358)			(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; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

We also find that robustness to random elimination of industries has a greater coefficient compared with robustness to the removal of the most connected industries. While this is admittedly unexpected, 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 shock propagation likely follows through related links early on, it does not necessarily follow the degree distribution of industries, especially when the outcome in terms of employment change is aggregated across years.

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, expanding on previous results showing that regions branching into more complex occupations also saw 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 the inclusion of 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 sign similar to that of 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, as industrial classifications tend to classify activities that use similar technologies together, this coefficient may express the downside of relatedness during crisis in terms of shared supplier linkages. In sum, 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), the last of which is a prominent predictor of employment outcomes during crisis. It should also be noted that, although only a limited number of conceptually relevant variables are included, R^2 is almost doubled in both cases compared to the initial OLS regressions.

We have tested the robustness of our findings to changes in key features of the analysis. In sum, these alternative specifications lent support to our main conclusions. 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 drove our results, we reran the models presented in Tables 1 and 2 after excluding these regions (SI Table 4). The findings of the main models remained in place, except that economic complexity (ECI_{2007}) lost its statistical significance, likely because complex economic activities tend to concentrate in large cities (Balland et al., 2020). Second, the capacity to tolerate random and targeted removal of industries entails two extreme cases for these local labour flow networks. Therefore, in a further test, we combined targeted and random removal (50% chance for either in a series of removals), leading to findings similar to those reported above (SI Table 3).

Third, our dependent variable covers the period 2007-2012, in an aim to capture the early stage of the crisis and its immediate aftermath. In a set of robustness checks, we tested whether the results would hold for alternative periods. As the main employment effects of the crisis were expressed in 2009 for the vast majority of Swedish regions (SI Figure 2), we tested an alternative period in which employment change between 2007 and 2009 is considered (SI Table 5). This would correspond to a conservative estimate of the resistance stage during this particular crisis, and has been used in previous studies on the resilience of Swedish regions (e.g., Martynovich et al., 2023). With respect to the beginning of the period, 2007 represents the last pre-crisis year in our main specifications. To test the robustness of this choice we reran our models using 2005 and 2006, respectively, as base years for calculating subsequent employment change. The results of these tests left our main findings in place.

Finally, we tested whether spatial dependence was an issue in our modelling setting. A mapping of the residuals from the main models reported in Tables 1 and 2 indicates that our models overall perform reasonably well in predicting employment change in crisis (SI Figure 3). Notable exceptions include the northern mining regions, which performed better in terms of resistance in employment compared with what we would expect based on their labour flow network structures, as well as some areas around the metro regions of Stockholm, Gothenburg and Malmö. The OLS models with LASSO selection tended to yield less extreme prediction errors for the mining regions in particular, also yielding a higher overall explained variance (see Adj. R^2 values in Tables 1 and 2), but with more regions with higher prediction errors compared with the basic OLS models. Additionally, we formally tested the local clustering of high and low values (Getis-Ord General G) of labour flow network robustness, as neighbouring regions may have developed labour-flow interactions between industries that would effectively create structural dependencies across these networks despite our using functional labour market regions as spatial units. However, as we find no statistically significant support for such local clustering of labour flow network robustness to either random or targeted elimination (SI Table 6), spatial dependence should not be an issue in our models.

5. Conclusion

In this paper we proposed an approach to engaging with which arrangements of interdependencies between local economic activities are conducive to resilience. This was done by drawing on advancements in evolutionary economic geography and the rich toolbox on network robustness developed in network science. The paper has thereby 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. As 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 than in others. Importantly, apart from a clear metropolitan premium, we find that this goes beyond being a matter of regional size, stressing instead that emergent local solutions to coordinating labour across economic activities yield structural strengths and vulnerabilities even among otherwise similar regions. We thereby advance previous studies based on nationwide relatedness (e.g., Sanchez-Moral et al., 2022) or a specific regional case (Gianelle, 2014). Given that the regional reallocation of workers is a prerequisite for smoothing the process of creative destruction at regional scale and lowering the adjustment costs for both individuals and society (Aghion et al., 2009), 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 through targeted retraining programmes 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 more slowly 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 structures 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 stream of empirical research 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). 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, which correspond to still open questions in the literature. First, our proposed measure of robustness was derived from a static network defined by normalised 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 changes of industrial compositions as well as the intensity of labour flows between pairs of industries, within the confines of this paper it was not possible to take up the task of exploring the dynamics of network robustness and its relation to resilience. 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 discuss dynamic processes of change to any greater degree. 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 have led to omitted variable bias. Considering both labour flows and supply chain connections in the same framework, however, might 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.

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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. Stepwise OLS model

SI Table 2. OLS regression results with stepwise introduction of variables.

	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					0.882*** (0.219)		1.996** (0.903)	
Ω^T						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; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$.

SI 3. 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 an optimisation problem similar to the one the Least Square estimator does, except that it includes a penalisation parameter:

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

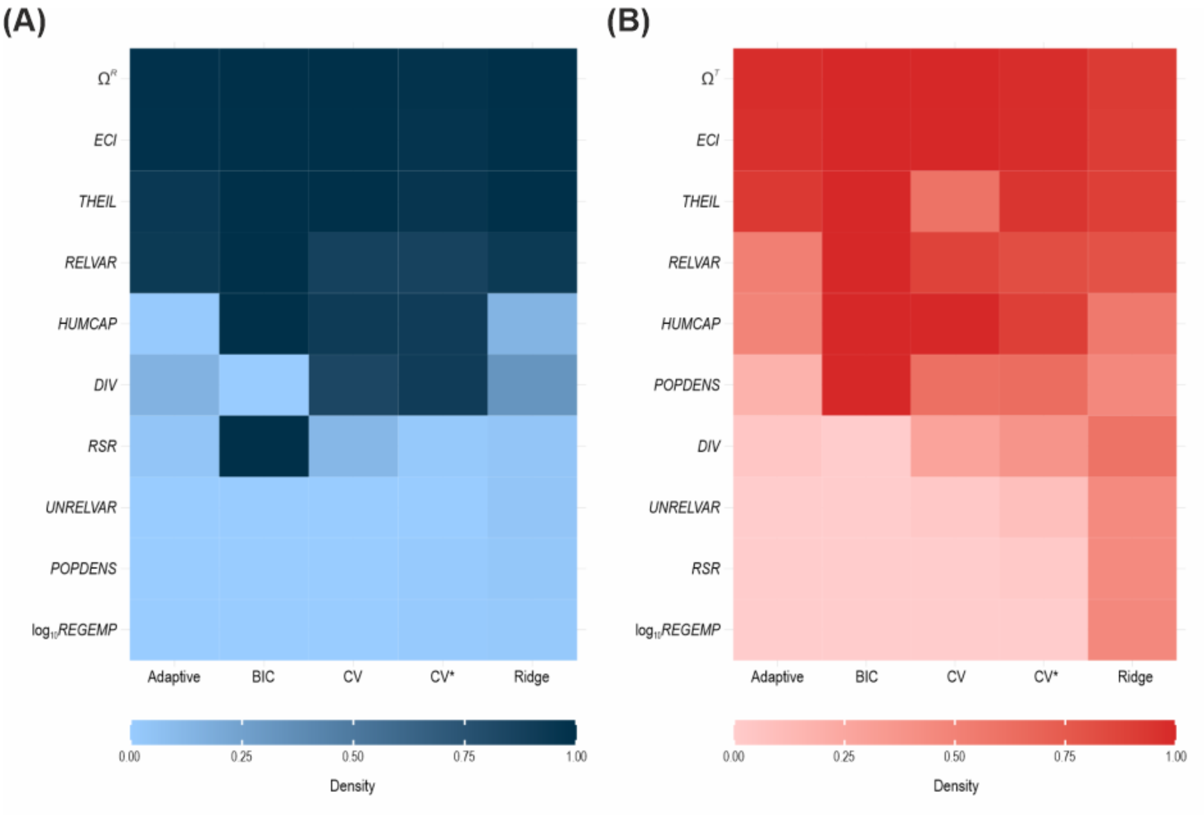
where the first term refers to the least-square optimisation process to minimise the squared residuals and the second term introduces the penalty term. In the penalty term, $\lambda \in \{0, \infty)$ is the LASSO penalisation parameter and ω_j is a parameter-level weight.

When λ takes the value of 0 the estimation reduces back the Least Square optimisation. With increasing values of λ, the degree of all the estimated coefficients diminishes towards 0. This 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 0. When we use LASSO for variable selection, the covariates with an estimated coefficient of 0 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 use Adaptive LASSO, 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 a sensitivity check, we apply other frequently used methods to ensure the consistency of our estimation. As the number of excluded covariates can be dependent on the value of λ, we use different versions of cross-validation (CV) to determine the optimal value of λ (Chetverikov et al., 2021). CV simulates the process of using split samples to optimise the most efficient out-of-sample predicators. The CV method identifies the optimal value of λ that minimises the out-of-sample mean squared error of the predictions and maximises 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). We 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 CV to refine the group of predictors to prevent overfitting; then the OLS we run with the selected set of variables should be free from overfitting bias (see Tables 1 and 2 in the main text). However, the variable selection depends on how we select the value of λ from SI Equation 1.

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 minimise the estimated out-of-sample prediction error. In this case, the optimal λ minimises 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 minimise the out-of-sample error. Another method for reducing the number of variables is Adaptive LASSO, which aims to find parsimonious models that might better reflect the true model. Adaptive LASSO also uses CV solutions, but it is a more conservative method as it selects a model with fewer covariates. For another robustness check we repeated the same exercise, but picked the λ with the minimum Bayes Information Criterion (BIC). Finally, as a complementary method, we used Ridge regression. In Ridge regression, the penalisation parameter from SI 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 that $\lambda \sum_{j=1}^{p} \omega_j \beta_j^2$. Ridge regression helps to shrink the coefficients, but rarely excludes variables from the model.



SI Figure 1. LASSO selection across different parametrisations.

Note: Blue corresponds to random elimination, red to targeted.

SI 4. Defining the variables of local industrial structure

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

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 industry groups. If every three-digit industry i falls under an industry group[2] S_g, where $g = 1, \ldots, G$, 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 three-digit employment shares:

$$P_g = \sum_{ieS_g} p_i \tag{3}$$

The entropy within each industry group S_g is H_g:

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

Unrelated variety ($UNRELVAR_r$) is measured as the entropy of the distribution of employment across industry groups in a region:

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

[2] The industry groups used for constructing alternative structural variables in this paper correspond with sections in the NACE Rev. 2 classification system, but are combined in some cases (e.g., ‘D - Electricity, gas, steam and air conditioning supply’ and ‘E - Water supply, sewerage, waste management and remediation activities’).

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 as it considers ex post relatedness, as opposed to deriving it from a classification scheme. It is defined formally as

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

Here, $SR_{ij,r}$is the inter-industry labour flow measure between three-digit industries i and $j \neq i$ that is present in region r, as described in Subsection 3.1 in the main text, 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 three-digit industry i from the total employment in region r, while N_r is the number of three-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 (one-step) neighbourhood of each industry, while our measure captures a more global structural feature of each labour flow network, at the local level.

Third, we follow the approach and formulation by Grillitsch et al. (2021) 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 industry group 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 industry group 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 ($M_{r,i}$), with each cell of the matrix showing 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 normalised between 0 and 1, essentially creating a ranking between regions based on their industrial structure (Mealy et al., 2019), whereby a higher value corresponds to a more complex economic structure. For a more detailed description of 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 5. Robustness checks

SI Table 3. Regression results with combined removal.

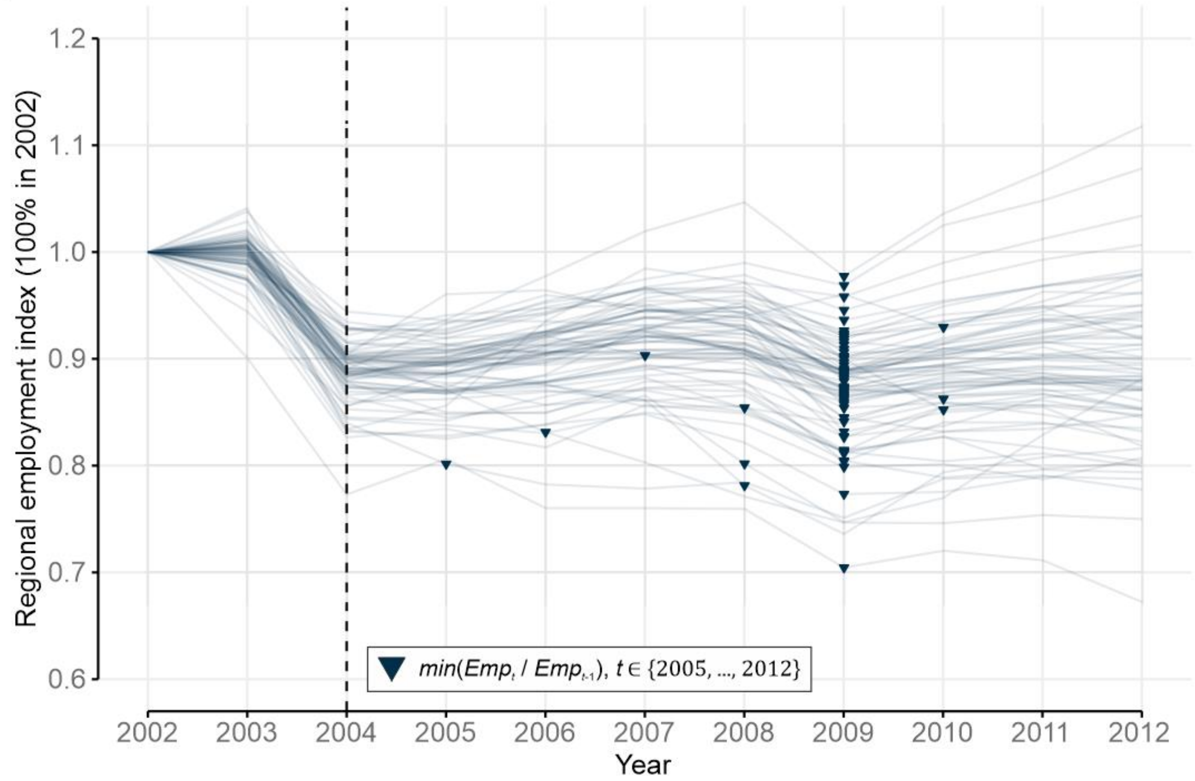
	Dependent variable: employment change 2007-2012				
	(1) OLS (baseline)	**(2)** OLS	**(3)** LASSO inference (adaptive)	**(4)** LASSO selection	**(6)** OLS with LASSO selection
$\log_{10} REGEMP_{2007}$	-0.041 (0.030)	0.029 (0.066)	0.006 (0.069)		
$POPDENS_{2007}$	0.000 (0.000)	-0.000 (0.000)	-0.000 (0.000)		
$HUMCAP_{2007}$	0.294* (0.151)	0.067 (0.169)	0.073 (0.156)		
Ω^C	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 4. 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	2.635** (0.910)		1.713*** (0.481)	
Ω^T		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 Figure 2. Employment change across functional labour markets in Sweden (100% in 2002).

SI Table 5. Results from OLS regression with LASSO selection for alternative periods.

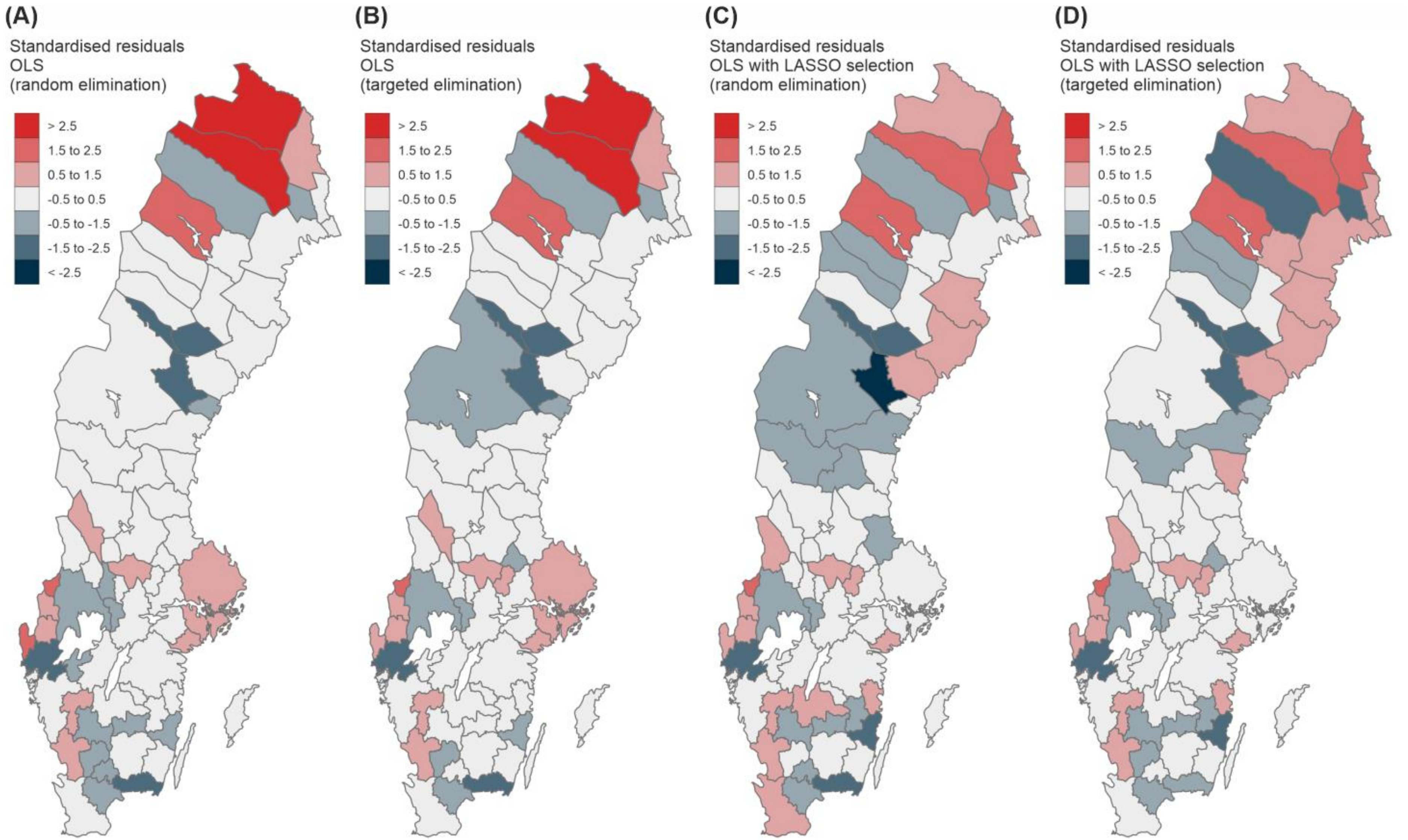
	Dependent variable: employment change											
	(1) 2007-2012	**(2)** 2006-2012	**(3)** 2005-2012	**(4)** 2007-2009	**(5)** 2006-2009	**(6)** 2005-2009	**(7)** 2007-2012	**(8)** 2006-2012	**(9)** 2005-2012	**(10)** 2007-2009	**(11)** 2006-2009	**(12)** 2005-2009
Ω^R	1.725*** (0.434)	1.740*** (0.512)	0.754** (0.352)	1.329*** (0.302)	1.196*** (0.318)	0.661*** (0.231)						
Ω^T							0.280*** (0.097)	0.328*** (0.107)	0.393*** (0.139)	0.217*** (0.068)	0.175*** (0.071)	0.258*** (0.095)
$RELVAR$	-0.066** (0.026)	-0.058* (0.031)		-0.048*** (0.018)	-0.046*** (0.017)							
$THEIL$	0.002* (0.001)	0.002* (0.001)		0.000 (0.000)			0.003*** (0.001)	0.003*** (0.001)	0.004*** (0.001)	0.001*** (0.000)	0.001* (0.001)	0.002*** (0.001)
ECI	0.092** (0.035)	0.122*** (0.041)	0.157*** (0.055)	0.044* (0.024)	0.057** (0.026)	0.083** (0.036)	0.091** (0.040)	0.117** (0.045)	0.135** (0.058)	0.045 (0.028)	0.064** (0.030)	0.080** (0.039)
Constant	0.423*** (0.125)	0.404*** (0.087)	0.667*** (0.141)	0.538*** (0.087)	0.404*** (0.087)	0.690*** (0.093)	0.874*** (0.026)	0.870*** (0.028)	0.900*** (0.035)	0.892*** (0.018)	0.870*** (0.028)	0.900*** (0.035)
# Region	72	72	72	72	72	72	72	72	72	72	72	72
R^2	0.446	0.447	0.302	0.429	0.367	0.316	0.377	0.405	0.366	0.336	0.296	0.323
Adjusted R^2	0.413	0.414	0.282	0.395	0.339	0.296	0.350	0.379	0.338	0.307	0.265	0.293
Mean VIF	3.69	3.87	1.50	3.69	3.73	1.50	1.67	1.62	1.70	1.67	1.62	1.70
F-Statistic	13.47***	13.53***	14.96***	12.57***	13.16***	15.95***	13.72***	15.45***	13.10***	11.48***	9.53***	10.79***

Note: Standard errors in parentheses; * $p < 0.1$; ** $p < 0.05$; *** $p < 0.01$. The final models of Tables 1 and 2 in the main text are repeated here in Columns 1 and 7 for convenience. $RELVAR$, $THEIL$ and ECI are measured in the starting year of the corresponding period. Variables are included only if they pass the selection criterion based on repeating the LASSO selection procedure described at the end of Subsection 3.3 and in SI 3.

SI Table 6. Getis-Ord General G high/low clustering analysis results.

	Ω^R	Ω^T
Observed General G	0.000	0.000
z-score	1.179	0.853
p-value	0.238	0.393

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



SI Figure 3. Spatial distribution of regression residuals.

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