Regional economic resilience, trophic characteristics, and ecological analogies

Anonymous Authors

August 2, 2023

Abstract

Works on regional resilience have at times borrowed from the engineering and ecological framing of system resilience. In ecological contexts, system resilience is rooted in network structure and its characteristics. Here, we empirically investigate the relationship between regional economic resilience and regional trophic characteristics across regional and national boundaries. We consider 249 NUTS2 regions across 24 countries during the 2000-2010 period. We observe strong links between regional resilience and trophic metrics borrowed from the ecological literature. Our results further highlight regional trophic characteristics as a spatially heterogeneous intermediary for feedback effects between economic structure and output of regions.

1 Introduction

Economic downturns and shocks, whatever their originating drivers may be, have a tendency to reignite scholarly interest in notions of regional and national resilience. Since the housing market crash and recession of 2008, an increasing number of contributions in economic geography have, to varying degrees, aligned their perspectives of resilience after those initiated in engineering and ecological traditions (Fingleton, Garretsen, & Martin, 2012). As it is often pointed out, across and within disciplines, resilience is defined in various subtly different ways (Punzo et al., 2020). What is common, however, is an association with systems' ability to withstand hardship and recover afterwards. In Ecology, resilience is the ability of species, and the ecosystem to which they belong, to withstand disruptive changes, eg, prolonged droughts or species and resource disappearance (Holling, 1973; Pimm, 1984), moving between equilibria. In Engineering, resilience is the ability of a system to withstand disruptions and quickly regain an acceptable level of performance (Hale & Heijer, 2006). Similar formulations have more recently made their way into the regional economics literature often portrayed as national or regional capacity to 'absorb' external shocks (Martin, 2012; Martin & Gardiner, 2019).

The overall understanding of resilience across the three traditions is fairly similar. And yet, there are crucial differences in expectations. Ecosystems, as complex systems in general, are more readily and frequently thought of as networks and modelled as such. This has offered ways of quantifying and more explicitly modelling their resilience as a function of their other structural characteristics (Levine, 1980; Pimm, 1984; Ulanowicz, Holt, & Barfield, 2014). In the economic literature, studies have looked at the potential effects of industry structure (Psycharis, Kallioras, & Pantazis, 2014; Han & Goetz, 2019; Delgado-Bello, Sáchez, & Ubeda, 2023), relatedness (Cainelli, Ganau, & Modica, 2019; Grabner & Modica, 2022), specialization and diversification (Palaskas, Psycharis, Rovolis, & Stoforos, 2015; Cuadrado-Roura & Maroto, 2016; Di Caro, 2017; J. Chen, Li, & Zhu, 2023), alongside considerations of urban/rural effects (Brakman, Garretsen, & van Marrewijk, 2015; Capello, Caragliu, & Fratesi, 2015; Grabner & Modica, 2022) as determinants of resilience. These have accumulated an abundance of evidence highlighting the degree to which resilience is affected by differences in structural composition of products and employment. Metrics used in such quantifications of relatedness, diversification, or specialization implicitly think of regional economies as networks in the same way that ecological studies do of food webs.

Trophic characteristics of food webs are similarly a collection of metrics that quantify the relationship between the species present in the system. Some articulate the position of individual species within the system, for example as a hierarchy of predation or contribution of biomass to other species, while others describe the overall nature and organization of the system. Over the last decade, the economic complexity community have to some extent attempted at better contextualizing more generic network formulations within the economics literature (Hidalgo & Hausmann, 2009; Hausmann & Hidalgo, 2011; Harvey & O'Neale, 2020; Bartesaghi, Clemente, Grassi, & Luu, 2022) beyond the surface-level parallels that go back to the works of Leontief and Ghosh on input-output (IO) models (Leontief, 1936; Ghosh, 1958; Manresa & Sancho, 2012). Such generic network structures have since been modified to codify and relate comparative advantage and relatedness of economic sectors and their products with regional growth and performance (Cicerone, McCann, & Venhorst, 2020). Though, missing is an examination of the original ecologically-derived generic structural metrics and resilience at a regional scale. This is despite McNerney (2018) having shown IO tables providing a readily mappable representation of economic systems within ecological traditions at national scales.

Here, we address the topic of regional economic resilience as a function of trophic characteristics derived from the ecological tradition. We believe this to be among the first such attempts. More specifically, we focus on the relationship between regional resilience and trophic length, depth, and coherence. We estimate these characteristics at a regional level based on intermediate tables of sectoral interactions within and across different national and regional economies. First, we demonstrate that resilient regions as a group consistently exhibit appreciably different trophic structures with longer trophic chains and more entangled sectoral connections. We further quantify the magnitude and direction of trophic effects on the likelihood of regional resilience using a simple logit formulation. Finally, we use the directionality of these relationships to identify direct and indirect regional structural feedback loops affecting regional and national economic performance. We show that regions with longer trophic chains are more likely to be resilient. Meanwhile, changes to the economic output or trophic structure of these regions could foreshadow change across a larger number of regions.

The rest of this paper is structured as follows. In the next section, we briefly outline the trophic characteristics considered, their ecological background, and methodological approach we use to estimate them. In the third and forth sections, we present and discuss the main empirical findings followed by a brief conclusion.

2 Trophic characteristics and related network abstraction of economic interactions

2.1 Trophic length and coherence

Trophic characteristics in systems ecology refer to metrics that quantify the position of various species within food chains/webs or ecosystems of which they are a member. In the context of food webs, networks codify the direction of predation, and sometimes their quantitative calorific nature, between the species involved in the system being studied. For these networks, trophic length/level, depth, and coherence are characteristics describing the position of a single species in the *chain*, the overall length of the *chain*, and how tidily the *chain* is stacked, respectively (Levine, 1980; Guimerà et al., 2010; Carscallen, Vandenberg, Lawson, Martinez, & Romanuk, 2012; Johnson, Domínguez-García, Donetti, & Muñoz, 2014). Let us demonstrate.

The predation relationship between species can be condensed in an adjacency matrix, $\boldsymbol{A}$, where entry a_{ij} is 1 if the specie on column j has the specie on row i in its diet, and zero otherwise. If quantities are known about the magnitude of predation, a weighted adjacency matrix, $\boldsymbol{W}$, could be used instead of $\boldsymbol{A}$. The trophic length, s_i, of each specie, i, in $\boldsymbol{W}$, or $\boldsymbol{A}$, can then be formalised as

$$s_i = 1 + \frac{1}{k_i^{in}} \sum_j w_{ij} s_j, \tag{1}$$

where w_{ij} is the corresponding entry of the network's weighted adjacency matrix, $\boldsymbol{W}$; s_j the trophic length of species j; and $k_i^{in} = \sum_j w_{ij}$ the overall predation pressure on specie i (Johnson et al., 2014; MacKay, Johnson, & Sansom, 2020). It is clear that the positions derived from Equation 1 are interdependent. To solve for all positions along the chain, species that do not prey on other members of the network are designated as primary producers and assigned a trophic length of 1. Figure 1 shows a series of toy food chains with 50 species ordered based on their trophic length, s.

Trophic coherence, meanwhile, provides a measure of the homogeneity of trophic distance, ie, $x_{ij} = s_i - s_j$, between species of different trophic length. This tidiness is measured as the standard deviation of trophic distances following

$$q = \sqrt{\left(\frac{1}{L}\sum_{i,j} w_{ij} x_{ij}^2\right) - 1}, \tag{2}$$

where $L = \sum_{i,j} w_{ij}$ is the total inter-species exchange/flow in the network and $q \in [0; +\infty)$ the system's trophic incoherence. A network is maximally coherent when $q = 0$ and becomes increasingly incoherent as q grows. Trophic incoherence articulates how distinctly the trophic lengths of species within a network are stacked with $q = 0$ representing a system where species fall within exactly a unit length of one another. Figure 1 demonstrates how different networks with the same number of species and universal preys can have a different overall depth, $\max(s)$, and coherence as a results of the structure of interactions between the other species. Maximum coherence, as is clear in the figure, requires compartmentalization of species such that there is no intra-compartment interactions and each compartment only preys on one other compartment of species. This level of network coherence is only likely when considering non-weighted representation of systems, $\boldsymbol{A}$. For empirical networks, eg, food chains with calorific information or those outside a food web context, incoherence is positive and its magnitude is an arbitrary function of network size and trophic lengths. In such cases, we can ascertain the robustness of the estimates of q through comparisons with the incoherence of a null model (Johnson & Jones, 2017). The null model expectation for network incoherence, $\tilde{q}$, can be calculated as

$$\tilde{q} = \sqrt{\frac{L}{L_b} - 1}, \tag{3}$$

where L_b is now the total flow involving only the primary producers within the network. If $q/\tilde{q} < 1$ the network is coherent, if $q/\tilde{q} > 1$ it is incoherent, and in the event $q/\tilde{q} = 1$ the network is as coherent as a randomly assembled network of the same size and composition is expected to be.

2.2 Empirical framework and implementation

The utility of trophic characteristics in ecological studies rests in how their analytical formulation links with ecosystem equilibria and resilience in systems where interactions can be modelled using non-linear differential equations, eg, Lotka–Volterra prey–predator models (Pimm, 1984; Gross, Rudolf, Levin, & Dieckmann, 2009; Ulanowicz et al., 2014; Fath et al., 2019). In this work, we are interested in exploring the impact of similar trophic characteristics when considering the resilience of regional economic systems where interaction dynamics cannot easily or neatly be modelled.

One simple mapping of trophic characteristics to regional economic system would involve treating either intermediate demand or supply tables as the standin for the calorifically-weighted species interaction matrix, $\boldsymbol{W}$. This will allow estimation of trophic length for individual sectors in each geography and trophic incoherence for the regions or nations to which they belong following Equations 1 and 2. For the results discussed in this work, we make use of the EUREGIO dataset which is a regionally extended version of the world input-output tables for European NUTS2 regional divisions (Thissen, Lankhuizen, van Oort, Los, & Diodato, 2018). The dataset has been previously used in analysing regional economic resilience, including regional exposure to Brexit (W. Chen et al., 2018), firm productivity and relatedness (Stavropoulos, van Oort, & Burger, 2020), and knowledge-based network structure and local productivity (Cortinovis & van Oort, 2019) among others. Detailed explanation on content and development of EUREGIO can be found in Thissen et *al.* (2018) and Chen et *al.* (2018).

We use the intermediate demand table from EUREGIO considering intersectoral trade structure of 14 industries within 249 NUTS2 geographies across 24 states between 2000 and 2010 recorded in million euros. The data set includes the overall global IO table at variable geographic resolutions with sectoral data for 24 EU states down to NUTS2 geographies, other major economies grouped nationally, and balancing the table with an aggregated rest-of-the-world geography. This means that our system for the EU between 2000 and 2010 includes 3486 unique *species* of 14 sectors across 249 NUTS2 regions that interact with one another, and other industry-geography species present in the EUREGIO intermediate table. Since there is no industry within intermediate demand tables that does not buy from any other industry, we do not assign any of the industrial species themselves as the peg for trophic length of 1. To provide a peg for the trophic length of 1, we look at employees as the in-context parallel for 'primary producer' specie, ie, nodes of trophic length 1 in Figure 2, using values of 'compensation of employees' for each regional sector from the dataset as a singular specie that is bought from by all sectors while not buying back within the context of an intermediate demand table.

When estimating s for each NUTS2 regional sector in the EU, we retain the entirety of the intermediate table including non-EU aggregated countries and rest-of-the-word, only rounding interactions to the nearest million euro as a pruning measure for relatively small interactions. This allows for a comparable estimation of trophic lengths across the entire network of the worldwide intermediate interactions. We should note that including geographically aggregated nodes from outside the EU, while preserving the hierarchy of the lengths, will to some extent squash the regional trophic length for sectors within the EU due to the larger magnitude of geographically aggregated sectoral flows. Figure 2B-C shows the distribution of regional trophic lengths estimated for the period 2000-2010.

What information, however, do these trophic lengths codify in the context of economic intermediate demand tables? Going back to the food web analogy, trophic depths provide an interpretation of system structure based on sectors/regions dependence on services of other sectors and/or regions. As such links are in the direction of services rendered, ie, opposite of monetary flows. This supply-position-from-demand perspective, is more intuitively picked up by considering how sectors like non-market services, distribution, and financial intermediation on average occupy shorter trophic lengths with their services in demand by other sectors compared with the mining and quarrying activities which have longer lengths and hence unlikely to be providing direct intermediate services demanded by many others, Figure 2C. Let's take the regions of Andalucia and Bratislavsky in Figure 2A as another example. Mining and quarrying sectors exhibit very different trophic characteristics in the two regions. In Andalucia, the sector occupies a length of $s = 3$ in the mid range of trophic lengths seen in the wider region indicating it both requires in services from other sectors/regions but also is a service provider to sectors/regions which would occupy trophic lengths higher than its own. The same sector in Bratislavsky, on the other hand, sits at the bottom of the region's trophic depth with $s \approx 7$. Considering very few sectors occupy lengths higher than $s = 7$, Figure 2C, the sector in Bratislavsky is likely not to be a popular and/or high volume service provider in the overall network. We can compare this with the position occupied by the Seagull in the toy food web in panel A. The regions as a whole exhibit this difference in overall position with sectors in Andalucia occupying shorter trophic lengths.

Unlike trophic length, we estimate the trophic incoherence, q, of each region individually by using only the sectoral intermediate interactions within the region for values of w_{ij} while using the trophic lengths obtained using the entirety of the intermediate table for values of x_{ij} in Equation 2. This allows us to retain the overall network information when considering the variance of the trophic lengths and how tidily they are stacked without retaining non-regional nodes outside the EU. Figure 3 shows the time series of trophic incoherence estimated both at national and regional boundaries for European states. We note here that considering a $q/\tilde{q}$ test, all regions considered throughout 2000-2010 exhibit $q/\tilde{q} > 1$. This indicates network structures to the right of Figure 1 and is in line with expectations from highly entangled networks of economic interactions, as compared with non-weighted symbolic representations of food webs. What is interesting, but to some extent trivial, to note is the dramatic disruption of trends in trophic incoherence following economic shocks in the data, ie, in 2002 and 2009, as intermediate sectoral/regional interactions undergo a restructuring following shocks. The restructuring in 2008-2009 saw a step drop in the trophic incoherence across the overwhelming majority of the regions considered. This could also reflect the ability of the network to respond to either shocks.[1] The *dotcom* crash of 2001 was significantly shorter, smaller, and more limited in its scope compared with the financial crisis in 2008 allowing for structural changes in the interactions as a means of responding and adjusting to the shock (Kliesen, 2003; Kose, Sugawara, & Terrones, 2020).

[1] It should be noted that the larger magnitude of the discontinuity in the 2001-2002 period could alternatively suggest changes in the data collection and treatment of the underlying IO tables(Lenzen, Pinto de Moura, Geschke, Kanemoto, & Moran, 2012).

2.3 IO models, inoperability, fragmentation, and other parallels

As previously suggested, surface level parallels between network representation of food webs and ecosystems and those of the intermediate demand/supply tables in IO models are relatively easy to draw. Before proceeding with the results, we briefly address the two main other bodies of work in economics that have similar or related perspectives.

The concept of inoperability and inoperability IO models were introduced in studies of risk and heavily borrowed from the engineering formulation of resilience. Defined as the "inability of the system to perform its intended function" (Haimes & Jiang, 2001), the models use variations of IO tables and multipliers in order to estimate the magnitude of this 'inability' treating shocks/events as changes to IO entries (Okuyama & Yu, 2019). Majority of recent activities in the space build upon existing inter-regional and inter-country IO studies and focus on examining the exposure of regions or sectors to the propagation of shocks throughout value-chains (Tian et al., 2022). As a method, similar to any IO model, the preoccupation is mostly with the quantification of the impacts, negative or positive, caused by this notional redistribution of consumption and not so much with the structure of the interactions (Oosterhaven, 2017). Typical insights from these studies point at the beneficial effect of supplier/client diversity, particularly when considering system resilience in the aftermath of environmental disasters (Todo, Nakajima, & Matous, 2015).

Fragmentation studies offer a perspective more concerned with the organization of interactions. They focus on the successive breakdown of production processes into stages the suppliers for which are highly clustered and differentiated in space and production stage. Works in this space are often concerned with measures of vertical specialization with empirical works looking at the share of domestic value-added in a unit of export. Conceptually, fragmentation is formulated as the position countries or regions take along production networks and is evidenced through increasingly denser connectivity of sectors/regions/countries in intermediate trade (Los, Timmer, & de Vries, 2015). Increased fragmentation is often cited to amplify effects of economic shocks as they propagate through increasingly clustered production stages nationally and regionally (Brakman, van Marrewijk, & Partridge, 2015). Fragmentation as a notion, unlike methods such as IO or inoperability, has closer conceptual ties with characteristics like trophic lengths and/or coherence although one-to-one mapping may not be immediately meaningful.

3 Results and Discussion

3.1 Trophic characteristics and regional economic output

We start by looking at the relationship between economic output and trophic length. We use values of the 'value-added' from EUREGIO as a proxy for economic output and performance at sector level and aggregated at regional and national levels. Previous work have already shown that, for inter-national IO structures, larger output multipliers are expected for nations of longer trophic length (McNerney et al., 2018).

For interactions in the EU over the 2000-2010 period, in addition to value-added itself, we calculate normalised economic output indexed against values at 2000, $\hat{Y} = \frac{Y^T}{Y^{2000}}$, and its year-on-year change, $\Delta\hat{Y}$. Figure 4 shows the link between mean trophic length of regions with their output and its growth. As shown in the figure, the overall magnitude of the output, on average, decreases with an increasing trophic length at both national and regional levels. While not a tight trend, particularly at a regional level, the shorter average position of sectors in regions with larger economies indicates larger intermediary roles for sectors making up these economies. Note that we calculate mean trophic length as the average of all sectoral lengths, s, throughout 2000-2010 and not the average of the regional trophic depth, $\max(s)$. The same mean trophic length, however, correlates positively with indicators of relative output growth and change. Regions and states that have on average sectors of greater length have had larger average growth rates and change relative to the starting point in 2000 Figure 4B-C.

What is worth pointing out here is the direction of relationship between trophic length and network incoherence. Averaged over time, similar metrics of relative growth for trophic length and incoherence are positively correlated at a regional level, Figure 5. This implies regions and nations on average lose network incoherence, ie, become more tidy in structure, when moving to the left of panels in Figure 4. Knowing that tidier structures require fewer interactions between sectors of similar lengths or hugely different lengths, regions and nations of shorter mean trophic lengths and/or with larger economies are likely to have more of a 'fragmented' sectoral dynamics internally.

3.2 Economic shocks, resilience, and trophic characteristics

Our main focus in this work is the impact of trophic characteristic of regional economic networks on their *relative* resilience evidencing and highlighting the network dynamics at play with regard to regional sectoral interactions. In considering resilience, we use a common formulation after (Martin, 2012; Lagravinese, 2015; Cainelli et al., 2019) looking at changes in economic output relative to the levels in a base year t following

$$Resilience_r^T = \frac{\dfrac{Y_r^T - Y_r^t}{Y_r^t} - \dfrac{Y_{EU}^T - Y_{EU}^t}{Y_{EU}^t}}{\left|\dfrac{Y_{EU}^T - Y_{EU}^t}{Y_{EU}^t}\right|} \tag{4}$$

where Y_r^T is the output of the region at year T, and Y_{EU} is the total EU-wide output. This allows for a relative and binary indication of resilience, R_r^T, for each region based on whether $Resilience_r^T$ is larger or smaller than zero

$$R_r^T = \begin{cases} 1 & Resilience_r^T > 0 \\ 0 & Resilience_r^T < 0 \end{cases} \tag{5}$$

where we conisder the region, r, to have been resilient if in time of economic prosperity, when the overall EU output increases, and in time of economic crisis, when the overall EU output declines, it shows a larger incremental growth or a smaller loss than the EU as a whole. While the formulation in Equation 4 can be used without alteration for both periods of contraction, as ability to resist shock, and expansion, as ability to recover, depending on the choice of t, the absolute magnitude of $Resilience_r^T$ could be very sensitive to this choice. For the rest of the analysis presented, we use a $t = 2000$. We note that there are various other definitions that could be used as a measure of regional resilience, particularly those that include comparisons with a presumed pre/post-shock growth paths (Fratesi & Perucca, 2018; Martin & Sunley, 2015). Here, we focus on the formulation presented in Equation 5 as it is provides a more convenient continuous measure that can be translated to whether or not a region is considered resilient, relatively speaking, rather than how resilient it may be in pair-wise comparisons with other regions.

We can now test for significant differentiation in trophic characteristics when grouping regions by resilience (Brown & Mood, 1951; Kruskal & Wallis, 1952). Resilient regions, as a cohort, consistently show both higher median trophic lengths and greater trophic depths when compared with non-resilient regions, Figure 6A-C. Through time, regions with economic networks of larger trophic lengths are more likely to belong to the group of resilient regions in that temporal snapshot. Given the coupling of trophic length and incoherence growth, a similar differentiation of regional resilience is seen with more incoherent regions more likely to belong to the resilient cohort. The larger trophic lengths and network incoherence in this context provide sector-level parallels for diversification arguments (Youn et al., 2016; Di Caro, 2017). It is likely that longer and less tidy intermediate consumption patterns allow for greater chances of substitution when the network is subject to stress. We should point out here that by using $t = 2000$ in Equation 4, it could be aregued that it measures the recovery and response to the 2008 crisis as part of the recovery from the much smaller 2000 crash and as such is, strictly speaking, measuring growth and not resilience. Nevertheless, the binary formulation in Equation 5 still provides a relative indication of resilience before an after shocks regardless of the base year used. See supplementary information for fairly similar variants of Figure 6A-C for two alternative estimates of resilience, one where we only consider year-on-year performance, ie, for each year we use the previous year as the base year, and one where we divide the period in three segments to capture the periods of contraction and expansion explicitly, ie, indexing 2001-2004 to $t = 2000$, 2005-2007 to $t = 2004$, and 2008-2010 to $t = 2007$ when the economy had peaked prior to the recession (Brakman, van Marrewijk, & Partridge, 2015).

The trophic-output relationship outlined in Figure 4 has further implications for regional expectations of resilience. Considering cohort-averaged characteristics in each annual snapshot during 2000-2010 also reveals a stark difference in the size of the economies and their growth rates. Panels D-F in Figure 6 suggest that, counter-intuitively, larger European regional economies are less likely to belong to the resilient cohort. This is despite the fact that the correlations seen in Figure 4 persist when considering the regional averages in both resilient and non-resilient cohorts, Figure 6.

To provide an estimation of the combined effects of the trophic characteristics on resilience, we examine a logit formulation for regional resilience à la (Cainelli et al., 2019) with a general form following

$$\text{Logit}(R_r^T) = \beta_0 + \beta_1 \bar{s}_r^T + \beta_2 \delta s_r^T + \beta_3 q_r^T \tag{6}$$

where, $\bar{s}_r^T$ is the average of sectoral trophic lengths in region r at time T, $\delta s_r^T = \max(s_r^T) - \min(s_r^T)$ the region's absolute length, and q_r^T its incoherence. Note that δs_r^T in effect measures the extent to which the sectoral networks are stretched across the trophic lengths in each region when considering the position of the region within the overall intermediate network containing all sectors/regions considered. We implement 7 variations of the model sequentially considering each independent variable and their combinations. Table 1 shows the model estimates for each variation including confidence intervals of the overall marginal effects for each variable. Before discussing the implications of the model, we have to note that we are not treating the dataset during 2000-2010 as a panel. For our estimates, we take each regional observation at a point in time as an independent data point fitting the model to the overall 2490 observations. In our case, this only causes negligible bias compared to fitting the model to data from each year separately or considering temporal lag effects explicitly. We would be remiss not to point out here that since we are not controlling for other regional characteristics in the results presented here, the following discussion is one of co-occurence between regional resilience and trophic characteristics and not one of implied causation. See supplementary information for a series of robustness checks where we control for year and additional regional variables with limited change to the direction of relationships reported for model 7. Datapoints are also available for independent testing.

Considering trophic characteristics individually and without controlling for others, chances of a region haveing faired better than the overall EU response in the same period increase with an increase in any of the three trophic variables considered, models 1-3. This is consistent with the bivariate observations for mean trophic length and the growth rate of normalised regional output. Although when considering the marginal effects, mean trophic length and regional absolute lengths have a noticeably larger impact on chances of resilience compared with network incoherence, with model 3 having also the lowest Pseudo-R^2 estimate of near zero. The most suitable model incorporating all three trophic variables, however, paints a slightly more nuanced picture. When considered together, resilience appears to favour regions that simultaneously have larger mean sectoral and absolute lengths but with a more organised and less incoherent structure.

In previous sections, we suggested that parallels exist between already explored economic metrics such as relatedness and trophic characteristics with similar expectations for potential effects of trophic incoherence and relatedness on resilience, which is in direct contrast to our observations here. While higher incoherence could imply higher interconnections, similar to relatedness, since the trophic characteristics are directional and capture the flow of services between trophic levels, in addition to from one industry to another, higher incoherence also implies a blurring of distinction between levels of service provision. This is not necessarily captured traditionally in measures of relatedness, diversification, or other measures of centrality. In more coherent systems, eg, the two left most networks in Figure 3, there is a more clear and apparent hierarchy of service relations where the sectors occupying a trophic level provide services to those in the level immediately above them and rely on services provided by those in the level immediately below them. The more coherent the network is, the less the chances that service provision in the system enters a loop or cycles; with sectors at higher differentiated levels providing termination points in the service provision paths within the intermediate supply tables. In a sense, supply-chain paths in coherent networks comprise linear one-way paths where intermediate services/products flow upward. It is then easy to see that while networks with increased incoherence are likely to see increased connections between sectors, unlike measures of relatedness, this increase is not necessarily accompanied by higher chances of technologically similar or equivalent industries which provide the intuition for the positive coupling of relatedness and resilience as redundancies in the system increase.

Regional mean trophic length and/or absolute length, on the other hand, are the metrics that perhaps explicitly capture the diversity of activities in the regions. The longer the trophic chain in a region, perhaps no matter how incoherent, the more *processed* the services moving up the trophic levels as the number of intermediary sectors increases. Or when considered in the context of all regions present, the higher the chances a region will have a service/product to provide, in any economic sector, for sectors of a given trophic level, ie, it will have a larger pool of potential customers and service providers. When considering regional resilience, the sectors in regions with a larger average sectoral length, $\bar{s}_r^T$, by definition, consume and benefit from a larger pool of sectors at lower trophic levels, whether within or without their home region, and as such have access to a larger pool of *substitutes*, whether it be a substitute sector or product/service, should shocks affect flow of products/services they rely on from levels below. Similarly, a larger absolute regional length, δs_r^T, would signal a similar potential for higher redundancy within the region, should there be strong enough intra-regional interactions between sectors along the length of trophic levels. This could also explain the observation in the supplementary material that in the presence of other control variables, only average trophic length retains its high explanatory power as it reflects both intra- and inter-regional possibilities rather than those existing only within a region.

Translating this back to the intermediary dynamics of sectors, regions appear to have better chances at resilience when their sectors are well integrated within the wider network. This requires a mix of sectors that strongly rely on services of other sectors interregionally, ie, have high trophic lengths, and those that are providers of such services. While this mirrors diversification arguments, the concurrent preference for low network incoherence suggests a degree of 'specialization' needed to ensure fragmentation across trophic levels. The fact that regional data considered shows an average increase in structural incoherence with an increase in mean trophic length suggests that, for the European regions considered, there exists a balance and trade-off between the two trophic characteristics in a pull-push effect regarding economic resilience.

3.3 Output-coherence directionality, feedback loops, and regional centrality in the EU

In this work so far, we have mostly highlighted the within-region coupling of trophic characteristics borrowed from system ecology and regional economic output and resilience in temporal snapshots. Looking at regional responses to the last four economic cycles up to the crash of 2008-09, (Martin, Sunley, Gardiner, & Tyler, 2016) have noted that it may be the inter/intra regional sectoral interactions that determine regional resiliency outcomes rather their economic structure, having found the latter to exhibit inconsistent spatial or temporal patterns. Given that regional sectoral trophic positions depend on intermediate sectoral interactions across all regions, the point of query can easily shift to whether changes in trophic characteristics in one region lead to performance changes in others. Finally, we consider this extension by considering potential bidirectional influence between the regional trophic incoherence and economic output on one another through time. We note here that our main point of interest is to investigate the existence and structure/geographies of these feedback loops between trophic incoherence and economic output rather than their magnitudes per se.

Considering regional value-added, we use Granger causality (Granger, 1969) to capture instances where trophic incoherence affects the time evolution of regional output and vice-versa. This allows us to create a characterisation of possible regional feedback loops both within the same NUTS2 region and across different regional pairs. The Granger causality assesses whether inclusion of a 'cause' variable affects the predictive power of an autoregressive model of an 'effect' variable (Granger, 1969). We conceptualize the feedback loops between regions as a bipartite network made of two sets of nodes, regional outputs and regional incoherences. For each pair of nodes, where each belongs to a different node set, we check whether one Granger-causes the other and vice versa. If yes, we consider a directed edge to exist between the two nodes capturing this effect, Figure 7A. This process involves checking for Granger-causality for 62001 (249×249) pairs of potential $Y - q$ Granger causalities and 62001 pairs of $q - Y$ Granger causalities. Note that for this, we only check that the null hypothesis of no Granger causality is rejected at a p-value < 0.05 threshold and not what the magnitude of the estimated coefficients for the lagged variables may be. Given the temporally limited number of observation for 2000-2010, we use a time lag of 3 years when checking for Granger causality (Barnett & Seth, 2014).

The resulting bipartite network, consisting of twice as many nodes as the number of the regions considered, is captured in an adjacency matrix, M_{qY} of size 498×498, where each non-zero entry represents a Granger causality between one region's output and another's incoherence or vice-versa. Note that M_{qY} does not contain any intra-compartment edges, see grey blocks in Figure 7A, and is not symmetrical acorss main diagonal as we capture the direction of Granger causality. Such a network can be used to identify regions that are potential intermediary actors or where the regional performance is particularly influenced by the network of relations with other European regions. To quantify these, we use the 'method of reflections' which in its generic form provides a means of examining the structure of bipartite networks. We first define

$$k_{rq,0} = \sum_{rY} M_{qY}\, , \text{and} \tag{7}$$

$$k_{rY,0} = \sum_{rq} M_{qY} \tag{8}$$

where r indexes NUTS2 regions considered. $k_{rq,0}$ and $k_{rY,0}$ are row sums that provide counts of regions influenced by a given region, r, and as such capture the diversity of regional outputs/incoherence Granger-caused by a region's trophic incoherence/output, respectively. From this starting point, as suggested by the method's name, we can examine the effects of the structure of our bipartite network of interactions by recursively tracking a number of *reflections*, n, from one compartment of nodes, ie, regional incoherence or output, to the other and back (see Figure 7B):

$$k_{rq,n} = \frac{1}{k_{rq,0}} \sum_{rY} M_{qY} k_{rY,n-1}, \text{and} \tag{9}$$

$$k_{rY,n} = \frac{1}{k_{rY,0}} \sum_{rq} M_{qY} k_{rq,n-1}. \tag{10}$$

Here, we focus on the first order reflection from one compartment to the other and back, $k_{rq,1}$ and $k_{rY,1}$, as higher order reflections will become increqasingly more difficult to tangibly interpret. $k_{rq,1}$ and $k_{rY,1}$ in essence capture how common a given region, r, is as potential Granger-effect of others, or how otherwise diverse, in the set of regions they potentially impact, the regions that Granger-cause a region's output are, respectively. It is important to remember that our approach quantifies the *potential* reach of regions rather than the magnitude of impact on other regions. The metrics allow identification of regions with potentially far reaching and/or unique regional influence as a function of the feedback loops embedded in the bidirectional influence of economic output and trophic incoherence. Figure 8 shows the spatial patterns of $k_{rq,0}$ and $k_{rY,1}$

for the European NUTS2 regions. It is worth noting that the underlying method to study bipartite networks is the same as that used by Hausmann and Hidalgo (2009; 2011) in their work on the diversity and complexity of nations' product space.

Through 2000-2010, Opole in Poland, Sardinia and Calabria in Italy, and Limousin in France had the highest above average number of Granger-links whereby changes in their trophic structure would affect economic output in other parts of the network. On the other hand, Liege and Western Flanders in Belgium, Central Bohemia in the Czech Republic, North Aegean in Greece, and many of the British regions had well below the average of number of regions within their network of trophic influence. Considering national averages and barring single region nations, Greece, Belgium, Czech Republic, and the UK showed limited regional infleunce in stark contrast with Denmark, Spain, and Italy.[2] Looking at the inset in Figure 8A, a larger network of influence nationally coincides with a larger mean growth rate of trophic length between 2000-2010. This reflects the higher chances of an economic ripple as regions move up the trophic levels and become dominant intermediary consumers of other sectors and regions. Finally, in panel B, we look at how unique these Granger-cause/effect relationships are between regions. Regions with a large $k_{rY,1}$ are one among many others that may be Granger-affected as part of a region's infleunce network, while those with a smaller $k_{rY,1}$, are either the sole region affected or one of a much smaller group of regions that may be affected. The inset also demosntrates that diveristy increases with a larger absolute regional trophic length when considering national averages. It is important to distinguish the dirversity and ubuiquity of these potential feedback loops and their strength. A peripherical region, say, Opole in Poland, that we have highlighted as exhibiting higher than average $k_{rq,0}$, has its trophic incoherence coupled with a larger than average number of regions' economic output, and hence a change in this region's trophic characteristics has a larger number of paths to cause feedback in the interregional network. This does not mean that changes to trophic incoherence of Opole have larger impacts on economic output of regions with which it is Granger-linked. Similarly, the mapping of $k_{rY,1}$ indicates the uniqueness of the region in terms of feedback loops arriving at them and not the strength of effects impacting them. Looking back at Table 1, however, the positive ifluence of δs on resilience can be seen reflected back in $k_{rY,1}$ as an increase in the number of alternative paths for shocks to flow through. It is worth noting that although $k_{rq,0}$ and $k_{rY,1}$ show coupling with trophic characteristics, their spatial patterns appear heterogeous without considerable clustering.

[2] It is important to clarify here that this does not mean that changes to trophic incoherence of these regions have impacts of smaller magnitude on economic output of other regions with which they are Granger-linked but rather they are Granger-linked with a smaller number of regions

4 Conclusions

Fundamental to linking general network-theoretic concepts and measures to ecological and then economic networks are the concepts of trophic length, depth, and coherence. In this paper, we set out to undertake a preliminary and empirical examination of whether ecological characteristics that provide theoretical underpinning for concepts of resilience in food webs show similar couplings with regional economic resilience when applied to interactions between regional economic sectors. As such, we have examined regional economic resilience as a function of these trophic characteristics of intermediate sectoral interactions and have shown considerable coupling between regional resilience and ecologically-defined characteristics, ie, trophic length, depth, and coherence. Our findings, here, make even more fitting the parallel between the regional economic network and trophic networks in natural ecosystems, where trophic length and coherence of the interactions determine how well species and the ecosystems to which they belong fare. The positive observation of these couplings would suggest that theoretical models that mechanistically link trophic characteristics to measures of their resilience may be adapted or mapped to regional economic structures. The potential for such interdisciplinary perspective could provide new insights and potentially similarly mechanistic models of dynamics within regional economies to complement the existing econometric evidence. Using the EUREGIO data from 2000 to 2010, we have analysed the effects of these characterics on the regional economic output and structure showing that following economic shocks, regional economic structures tend to re-organise with faster-growing economies extending their trophic length and depth within the overall network of intermediary interactions. Looking specifically at regional resilience, we have also shown a trade-off effect to exist between diversification and specialisation when considering regional resilience using ecologically-inspired characteristics. Lastly, we mapped the feedback effects that exist, as a result of the bidirectional influence of trophic characteristics and economic ouput on one another, and their impact on regional resilience.

Acknowledgements

Maps of the EU contain Eurostat statistical units © EuroGeographics for the administrative boundaries.

Conflict of interest

The authors declare no conflicting interests.

Supporting Information

Electronic supplementary material including the script used to perform the analysis and prepare the figures is available online at REDACTED FOR BLINED REVIEW.

References

Barnett, L., & Seth, A. K. (2014, February). The MVGC multivariate Granger causality toolbox: A new approach to Granger-causal inference. *Journal of Neuroscience Methods*, *223*, 50–68. doi: 10.1016/j.jneumeth.2013.10.018

Bartesaghi, P., Clemente, G. P., Grassi, R., & Luu, D. T. (2022, December). The multilayer architecture of the global input-output network and its properties. *Journal of Economic Behavior & Organization*, *204*, 304–341. doi: 10.1016/j.jebo.2022.10.029

Brakman, S., Garretsen, H., & van Marrewijk, C. (2015, July). 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. doi: 10.1093/cjres/rsv005

Brakman, S., van Marrewijk, C., & Partridge, M. (2015). Local Consequences of Global Production Processes. *Journal of Regional Science*, *55*(1), 1–9. doi: 10.1111/jors.12179

Brown, G. W., & Mood, A. M. (1951, January). On Median Tests for Linear Hypotheses. *Proceedings of the Second Berkeley Symposium on Mathematical Statistics and Probability*, *2*, 159–167.

Cainelli, G., Ganau, R., & Modica, M. (2019). Industrial relatedness and regional resilience in the European Union. *Papers in Regional Science*, *98*(2), 755–778. doi: 10.1111/pirs.12377

Capello, R., Caragliu, A., & Fratesi, U. (2015, September). Spatial heterogeneity in the costs of the economic crisis in Europe: Are cities sources of regional resilience? *Journal of Economic Geography*, *15*(5), 951–972. doi: 10.1093/jeg/lbu053

Carscallen, W. M. A., Vandenberg, K., Lawson, J. M., Martinez, N. D., & Romanuk, T. N. (2012). Estimating trophic position in marine and estuarine food webs. *Ecosphere*, *3*(3), art25. doi: 10.1890/ES11-00224.1

Chen, J., Li, X., & Zhu, Y. (2023). Shock absorber and shock diffuser: The multiple roles of industrial diversity in shaping regional economic resilience after the Great Recession. *The Annals of Regional Science*. doi: 10.1007/s00168-023-01233-2

Chen, W., Los, B., McCann, P., Ortega-Argilés, R., Thissen, M., & van Oort, F. (2018). The continental divide? Economic exposure to Brexit in regions and countries on both sides of The Channel. *Papers in Regional Science*, *97*(1), 25–54. doi: 10.1111/pirs.12334

Cicerone, G., McCann, P., & Venhorst, V. A. (2020, January). Promoting regional growth and innovation: Relatedness, revealed comparative advantage and the product space. *Journal of Economic Geography*, *20*(1), 293–316. doi: 10.1093/jeg/lbz001

Cortinovis, N., & van Oort, F. (2019, November). Between spilling over and boiling down: Network-mediated spillovers, local knowledge base and productivity in European regions. *Journal of Economic Geography*, *19*(6), 1233–1260. doi: 10.1093/jeg/lby058

Cuadrado-Roura, J. R., & Maroto, A. (2016, March). Unbalanced regional resilience to the economic crisis in Spain: A tale of specialisation and productivity. *Cambridge Journal of Regions, Economy and Society*, *9*(1), 153–178. doi: 10.1093/cjres/rsv034

Delgado-Bello, C., Sáchez, A. M., & Ubeda, M. A. (2023). Resilience and economic structure: The case of the Chilean regions during the Asian crises and the Great Recession of 2008. *Papers in Regional Science*, *102*(1), 31–51. doi: 10.1111/pirs.12719

Di Caro, P. (2017). Testing and explaining economic resilience with an application to Italian regions. *Papers in Regional Science*, *96*(1), 93–113. doi: 10.1111/pirs.12168

Fath, B., Asmus, H., Asmus, R., Baird, D., Borrett, S., de Jonge, V., ... Wolff, M. (2019, May). Ecological network analysis metrics: The need for an entire ecosystem approach in management and policy. *Ocean and Coastal Management*, *174*, 1–14. doi: 10.1016/j.ocecoaman.2019.03.007

Fingleton, B., Garretsen, H., & Martin, R. (2012). Recessionary Shocks and Regional Employment: Evidence on the Resilience of U.K. Regions. *Journal of Regional Science*, *52*(1), 109–133. doi: 10.1111/j.1467-9787.2011.00755.x

Fratesi, U., & Perucca, G. (2018). Territorial capital and the resilience of European regions. *The Annals of Regional Science*, *60*(2), 241–264. doi: 10.1007/s00168-017-0828-3

Ghosh, A. (1958). Input-Output Approach in an Allocation System. *Economica*, *25*(97), 58–64. doi: 10.2307/2550694

Grabner, S. M., & Modica, M. (2022). Industrial resilience, regional diversification and related variety during times of crisis in the US urban–rural context. *Regional Studies*, *56*(10), 1605–1617. doi: 10.1080/00343404.2021.2002837

Granger, C. W. J. (1969). Investigating causal relations by econometric models and cross-spectral methods. *Econometrica : journal of the Econometric Society*, *37*(3), 424–438.

Gross, T., Rudolf, L., Levin, S. A., & Dieckmann, U. (2009, August). Generalized Models Reveal Stabilizing Factors in Food Webs. *Science*, *325*(5941), 747–750. doi: 10/d8qfsb

Guimerà, R., Stouffer, D. B., Sales-Pardo, M., Leicht, E. A., Newman, M. E. J., & Amaral, L. a. N. (2010, October). Origin of compartmentalization in food webs. *Ecology*, *91*(10), 2941–2951. doi: 10/c9sb6r

Haimes, Y. Y., & Jiang, P. (2001, March). Leontief-Based Model of Risk in Complex Interconnected Infrastructures. *Journal of Infrastructure Systems*, *7*(1), 1–12. doi: 10.1061/(ASCE)1076-0342(2001)7:1(1)

Hale, A., & Heijer, T. (2006). Defining Resilience. In E. Hollnagel, D. Woods, & N. Leveson (Eds.), *Resilience engineering: Concepts and precepts* (pp. 35–41). Hampshire, UK: Ashgate Publishing Ltd.

Han, Y., & Goetz, S. J. (2019). Predicting US county economic resilience from industry input-output accounts. *Applied Economics*, *51*(19), 2019–2028. doi: 10.1080/00036846.2018.1539806

Harvey, E. P., & O'Neale, D. R. J. (2020). Using Network Science to Quantify Economic Disruptions in Regional Input-Output Networks. In N. Masuda, K.-I. Goh, T. Jia, J. Yamanoi, & H. Sayama (Eds.), *Proceedings of NetSci-X 2020: Sixth International Winter School and Conference on Network Science* (pp. 259–270). Cham: Springer International Publishing. doi: 10.1007/978-3-030-38965-$9_1$8

Hausmann, R., & Hidalgo, C. A. (2011, December). The network structure of economic output. *Journal of Economic Growth*, *16*(4), 309–342. doi: 10/c79ftn

Hidalgo, C. A., & Hausmann, R. (2009, June). The building blocks of economic complexity. *Proceedings of the National Academy of Sciences*, *106*(26), 10570–10575. doi: 10/fpzkth

Holling, C. S. (1973). Resilience and Stability of Ecological Systems. *Annual Review of Ecology and Systematics*, *4*(1), 1–23. doi: 10.1146/annurev.es.04.110173.000245

Johnson, S., Domínguez-García, V., Donetti, L., & Muñoz, M. A. (2014, December). Trophic coherence determines food-web stability. *Proceedings of the National Academy of Sciences*, *111*(50), 17923–17928. doi: 10/f8mmbf

Johnson, S., & Jones, N. S. (2017, May). Looplessness in networks is linked to trophic coherence. *Proceedings of the National Academy of Sciences*, *114*(22), 5618–5623. doi: 10.1073/pnas.1613786114

Kliesen, K. L. (2003). The 2001 recession: How was it different and what developments may have caused it? *Review*, *85*(Sep), 23–38.

Kose, M. A., Sugawara, N., & Terrones, M. E. (2020, February). *Global Recessions* (Tech. Rep. No. 2002). Koc University-TUSIAD Economic Research Forum.

Kruskal, W. H., & Wallis, W. A. (1952, December). Use of Ranks in One-Criterion Variance Analysis. *Journal of the American Statistical Association*, *47*(260), 583–621. doi: 10.1080/01621459.1952.10483441

Lagravinese, R. (2015, July). Economic crisis and rising gaps North–South: Evidence from the Italian regions. *Cambridge Journal of Regions, Economy and Society*, *8*(2), 331–342. doi: 10.1093/cjres/rsv006

Lenzen, M., Pinto de Moura, M. C., Geschke, A., Kanemoto, K., & Moran, D. D. (2012, December). A Cycling Method for Constructing Input–Output Table Time Series from Incomplete Data. *Economic Systems Research*, *24*(4), 413–432. doi: 10.1080/09535314.2012.724013

Leontief, W. W. (1936). Quantitative Input and Output Relations in the Economic Systems of the United States. *The Review of Economics and Statistics*, *18*(3), 105–125. doi: 10.2307/1927837

Levine, S. (1980, March). Several measures of trophic structure applicable to complex food webs. *Journal of Theoretical Biology*, *83*(2), 195–207. doi: 10.1016/0022-5193(80)90288-X

Los, B., Timmer, M. P., & de Vries, G. J. (2015). How Global Are Global Value Chains? A New Approach to Measure International Fragmentation. *Journal of Regional Science*, *55*(1), 66–92. doi: 10.1111/jors.12121

MacKay, R. S., Johnson, S., & Sansom, B. (2020). How directed is a directed network? *Royal Society Open Science*, *7*(9), 201138. doi: 10.1098/rsos.201138

Manresa, A., & Sancho, F. (2012, October). *Leontief versus Ghosh: Two faces of the same coin* (Tech. Rep. No. XREAP2012-18). Xarxa de Referència en Economia Aplicada (XREAP).

Martin, R. (2012, January). Regional economic resilience, hysteresis and recessionary shocks. *Journal of Economic Geography*, *12*(1), 1–32. doi: 10.1093/jeg/lbr019

Martin, R., & Gardiner, B. (2019). The resilience of cities to economic shocks: A tale of four recessions (and the challenge of Brexit). *Papers in Regional Science*, *98*(4), 1801–1832. doi: 10.1111/pirs.12430

Martin, R., & Sunley, P. (2015, January). On the notion of regional economic resilience: Conceptualization and explanation. *Journal of Economic Geography*, *15*(1), 1–42. doi: 10.1093/jeg/lbu015

Martin, R., Sunley, P., Gardiner, B., & Tyler, P. (2016, April). How Regions React to Recessions: Resilience and the Role of Economic Structure. *Regional Studies*, *50*(4), 561–585. doi: 10.1080/00343404.2015.1136410

McNerney, J., Savoie, C., Caravelli, F., & Farmer, J. D. (2018, October). How production networks amplify economic growth. *arXiv:1810.07774 [physics, q-fin]*.

Okuyama, Y., & Yu, K. D. (2019, October). Return of the inoperability. *Economic Systems Research*, *31*(4), 467–480. doi: 10.1080/09535314.2018.1510383

Oosterhaven, J. (2017, July). On the limited usability of the inoperability IO model. *Economic Systems Research*, *29*(3), 452–461. doi: 10.1080/09535314.2017.1301395

Palaskas, T., Psycharis, Y., Rovolis, A., & Stoforos, C. (2015, September). The asymmetrical impact of the economic crisis on unemployment and welfare in Greek urban economies. *Journal of Economic Geography*, *15*(5), 973–1007. doi: 10.1093/jeg/lbv027

Pimm, S. L. (1984, January). The complexity and stability of ecosystems. *Nature*, *307*(5949), 321–326. doi: 10.1038/307321a0

Psycharis, Y., Kallioras, D., & Pantazis, P. (2014). Economic crisis and regional resilience: detecting the 'geographical footprint' of economic crisis in Greece. *Regional Science Policy & Practice*, *6*(2), 121–141. doi: 10.1111/rsp3.12032

Punzo, G., Tewari, A., Butans, E., Vasile, M., Purvis, A., Mayfield, M., & Varga, L. (2020, September). Engineering Resilient Complex Systems:

The Necessary Shift Toward Complexity Science. *IEEE Systems Journal*, *14*(3), 3865–3874. doi: 10.1109/JSYST.2019.2958829
Stavropoulos, S., van Oort, F. G., & Burger, M. J. (2020, October). Heterogeneous relatedness and firm productivity. *The Annals of Regional Science*, *65*(2), 403–437. doi: 10.1007/s00168-020-00988-2
Thissen, M., Lankhuizen, M., van Oort, F., Los, B., & Diodato, D. (2018, November). *EUREGIO: The Construction of a Global IO Database With Regional Detail for Europe for 2000–2010* (SSRN Scholarly Paper No. 3285818). Rochester, NY. doi: 10.2139/ssrn.3285818
Tian, K., Zhang, Z., Zhu, L., Yang, C., He, J., & Li, S. (2022, July). Economic exposure to regional value chain disruptions: Evidence from Wuhan's lockdown in China. *Regional Studies*, 1–12. doi: 10.1080/00343404.2022.2078802
Todo, Y., Nakajima, K., & Matous, P. (2015). How Do Supply Chain Networks Affect the Resilience of Firms to Natural Disasters? Evidence from the Great East Japan Earthquake. *Journal of Regional Science*, *55*(2), 209–229. doi: 10.1111/jors.12119
Ulanowicz, R. E., Holt, R. D., & Barfield, M. (2014, February). Limits on ecosystem trophic complexity: Insights from ecological network analysis. *Ecology Letters*, *17*(2), 127–136. doi: 10/f5nndh
Youn, H., Bettencourt, L. M. A., Lobo, J., Strumsky, D., Samaniego, H., & West, G. (2016, January). Scaling and universality in urban economic diversification. *Journal of The Royal Society Interface*, *13*(114), 20150937. doi: 10/gc4nwq

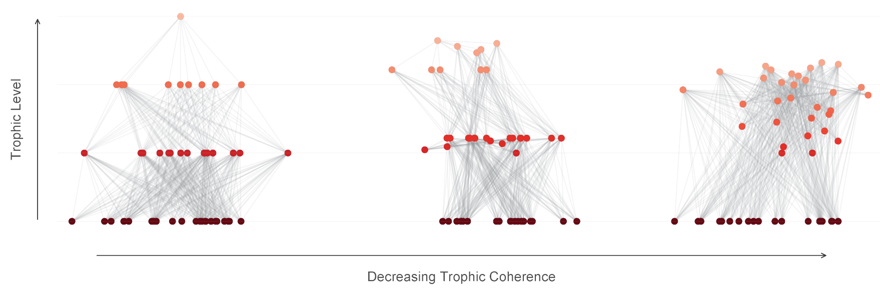

Figure 1: Schematic representation of a toy network of 50 species with differing trophic lengths and coherence structure. Grid lines from top to bottom denote $s = 1, 2, 3, 4$ and with networks having an increasing value of q from left to right.

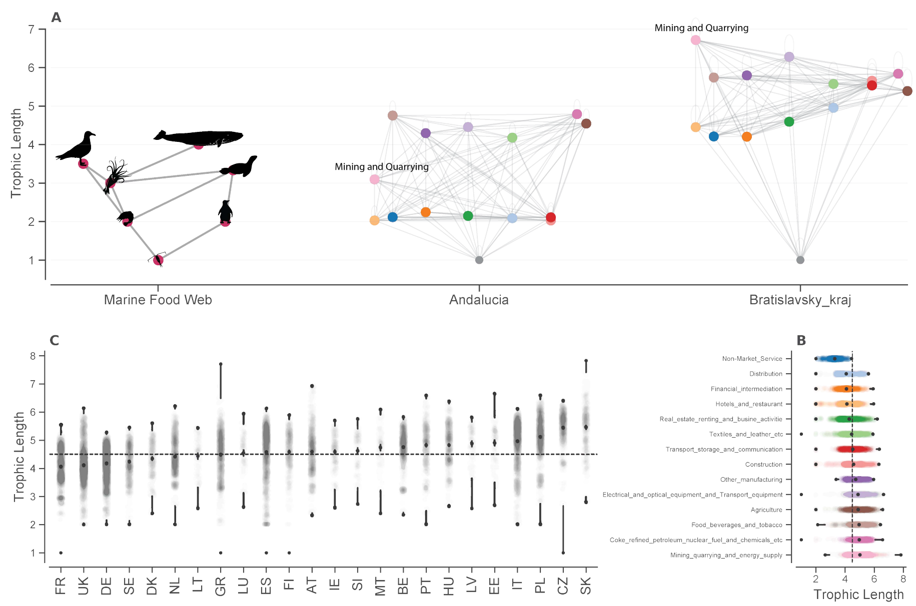

Figure 2: 2000-2010 mean sectoral trophic length for two regions of typically short and long trophic depths as compared with an un-weighted toy food web (A), distribution of trophic lengths grouped by country (B) and grouped by economic sector (C) showing mean, min, max, and their 95% confidence intervals – dashed lines indicate overall mean.

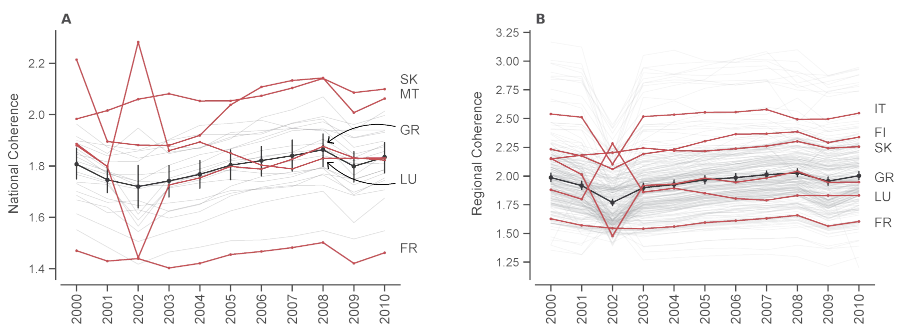

Figure 3: Lineplots showing the national (A) and regional (B) incoherence, q with black points and error bars showing EU-wide mean and its 95%CI.

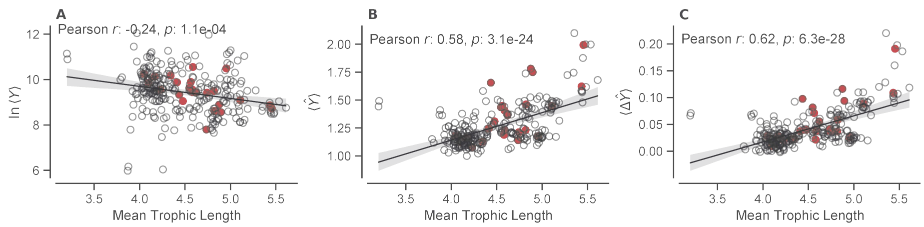

Figure 4: Panels A through C showing the correlation between 2000-2010 time-averaged overall output, Y, 2000-normalised output, $\hat{Y}$, and growth, $\Delta\hat{Y}$, with mean trophic length for NUTS2 regions – solid red points show national averages.

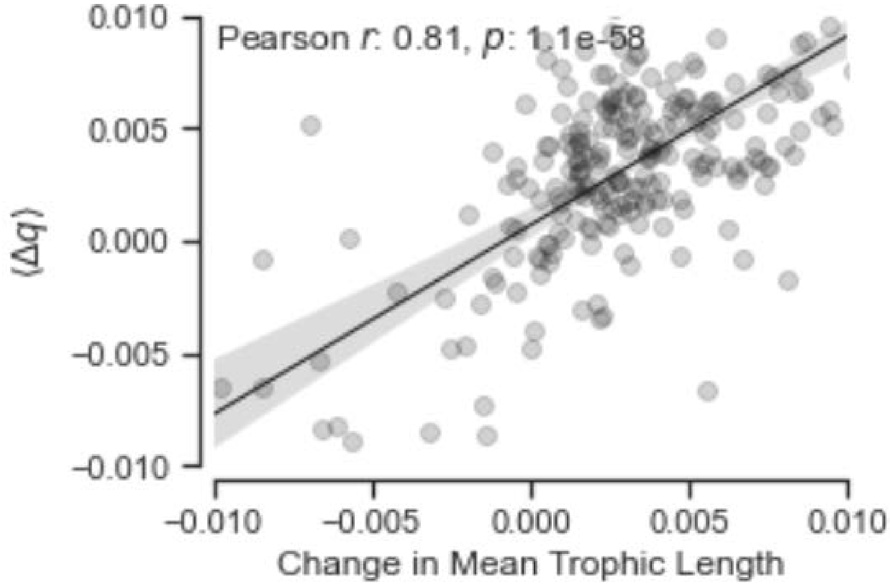

Figure 5: Scatterplot of change in time-averaged mean trophic length versus change in incoherence at NUTS2 level.

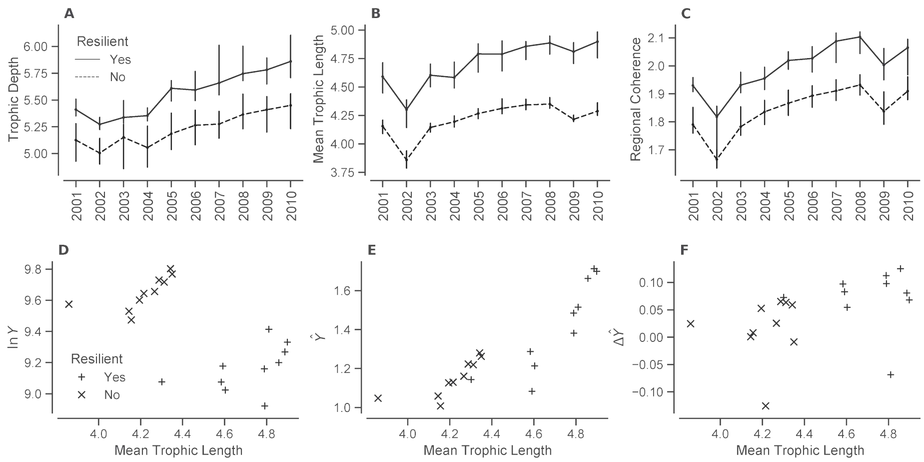

Figure 6: Panels A through C showing the median and its 95%CI for trophic depth, $\max(s)$, mean trophic length, $\bar{s}$, and incoherence, q, for regions grouped based on resilience for the period starting in 2000–note that for the exception of 2002 in panel C, the two groups are statistically differentiated following both Mood's median and Kruskal–Wallis test with $p \ll 0.01$. Panels D through F showing variations of output, Y, normalised output, $\hat{Y}$, and its annual change, $\Delta\hat{Y}$, against mean trophic length from panel B.

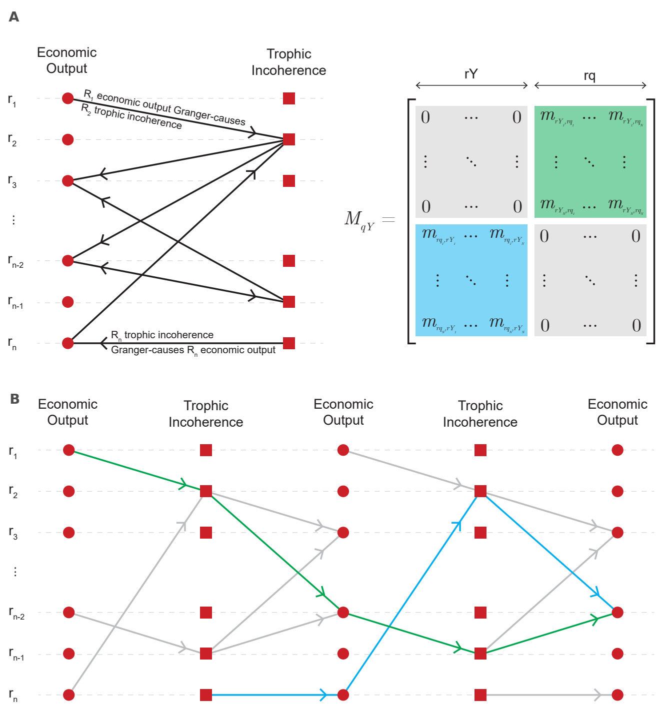

Figure 7: Schematic showing the assembly of a bipartite $q - Y$ regional influence network based on Granger-causality between the two sets of variables between 2000-2010 (A) and an example of resulting paths of feedback *reflected* through the layers (B).

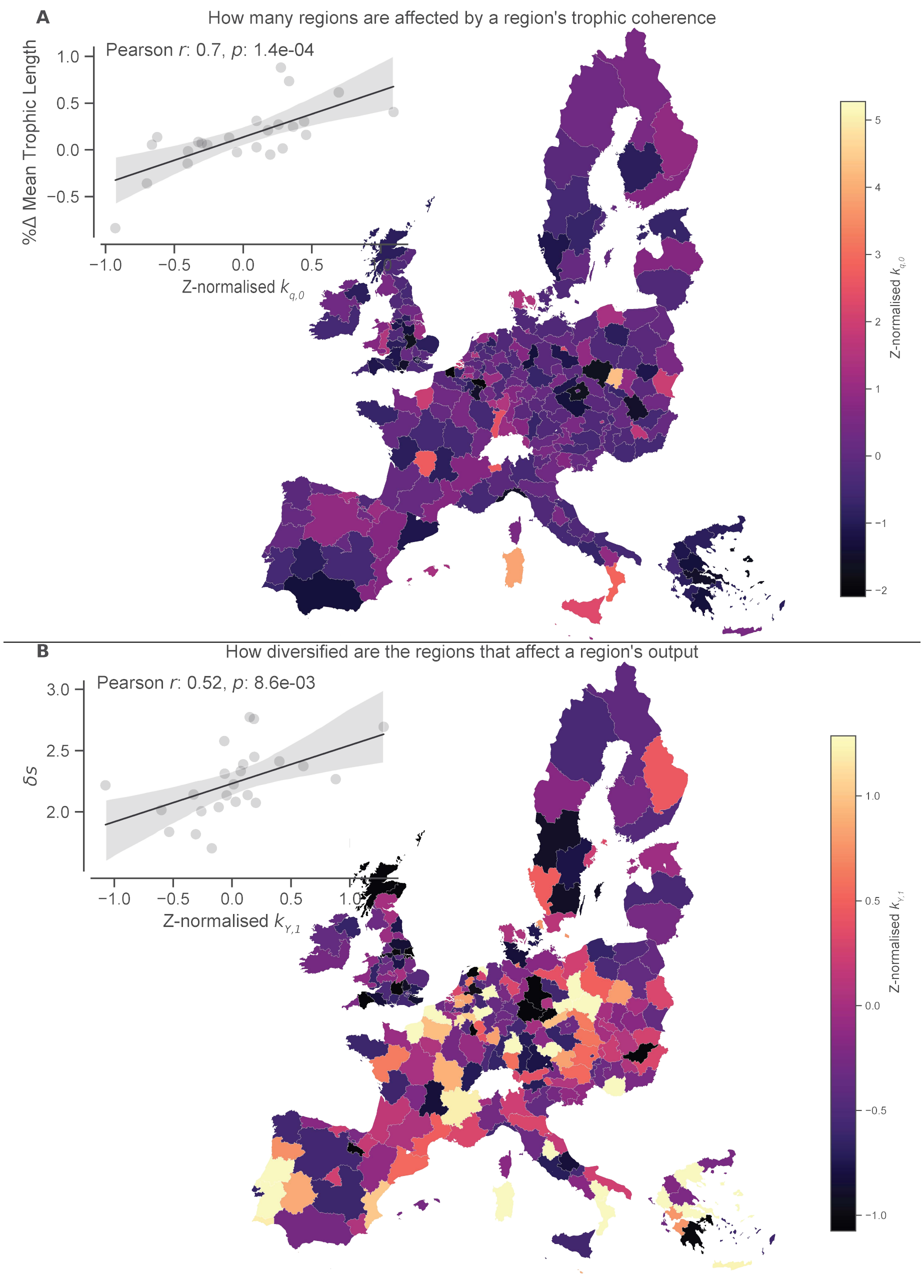

Figure 8: Regional distribution of $k_{q,0}$ highlighting regions with above/below average influence (A) and $k_{Y,1}$ showing how diversified the trophic influencer that affect a region's output are (B) – the insets show the correlation between time-averaged change in regional mean trophic length and $k_{q,0}$ (A) and between in regional absolute trophic length and $k_{Y,1}$ (B) aggregated nationally.

Table 1: Logit model results of regional resilience against the combination of predictors in Eq. 6 showing direct estimates for coefficients and their overall marginal effects.

n=2490	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7†
Pseudo-R^2	0.09	0.06	0.01	0.13	0.11	0.06	0.15
$\bar{s}_r^T$	0.76***			0.70***	1.13***		1.14***
	(0.05)			(0.05)	(0.08)		(0.07)
	[0.66, 0.86]			[0.61, 0.80]	[0.97, 1.28]		[1.00, 1.28]
$\partial y/\partial \bar{s}_r^T$	[0.15, 0.18]			[0.13, 0.16]	[0.22, 0.27]		[0.21, 0.25]
δs_r^T		0.62***		0.53***		0.59***	0.60***
		(0.05)		(0.05)		(0.05)	(0.05)
		[0.52, 0.73]		[0.44, 0.63]		[0.49, 0.69]	[0.50, 0.70]
$\partial y/\partial \delta s_r^T$		[0.12, 0.17]		[0.09, 0.13]		[0.12, 0.16]	[0.10, 0.14]
q_r^T			0.26***		-0.49***	0.19***	-0.58***
			(0.05)		(0.07)	(0.05)	(0.07)
			[0.17, 0.35]		[-0.63, -0.35]	[0.10, 0.28]	[-0.71, -0.45]
$\partial y/\partial q_r^T$			[0.04, 0.09]		[-0.13, -0.08]	[0.02, 0.06]	[-0.14, -0.09]
β_0	-0.10	-0.08	-0.09	-0.09	-0.09	-0.08	-0.08
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.05)
	[-0.18, -0.02]	[-0.16, 0.00]	[-0.17, -0.02]	[-0.18, -0.01]	[-0.17, -0.01]	[-0.17, 0.00]	[-0.17, 0.00]

†model with lowest values of AIC and BIC.

***p-value$\ll 0.001$, $(\cdot)$ denotes standard errors, and $[\cdot,\cdot]$ the 95% confidence intervals.