

Devising a net zero resilience index: A note on methods

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About the research

The UK's transition to net zero will create new economic opportunities, but will also have a negative impact on jobs in regions with carbon-intensive economic activity. This will require policies to mitigate the impacts. An estimated 7% of the UK workforce will be exposed to potential changes in employment opportunities (approximately 2.2 million people). Proactive policies today can be devised to diversify local economies and support communities facing this change.

Researchers at the University of Bristol have developed a [net-zero resilience index](#) (NZRI) to reveal the people and places where the economic impacts of net zero will likely be clustered. It has highlighted 32 Local Authorities that may be particularly vulnerable to economic shocks from net zero policy and may require additional support to ensure greater resilience.

The NZRI draws from theory and methods in complexity economics and hazard-risk. This short methods note – accompanying a [briefing outlining key findings](#) – outlines the approach in more detail to allow greater transparency and replicability.

Components of the net zero resilience index

The net zero resilience index is formed of four components: Reliance, Complexity, Relatedness, and Working Age Population (see Figure 1).

Reliance captures the extent to which employment in a Local Authority area is reliant on high-emission sectors. The assumption is that policies to reduce emissions are likely to have an impact on these sectors. This component uses Standard Industrial Classification codes for sectors identified by the [UK Climate Change Committee](#) and [HM Treasury work](#). Employment numbers are taken from the [2022-2023 Business Register and Employment Survey](#). The following sectors are considered high-emissions in the analysis:

- Coal production
- Energy intensive industry
- Gas distribution
- Livestock and mixed agriculture
- Oil and gas production
- Retail fuel
- Vehicle manufacturing
- Vehicle maintenance
- Waste

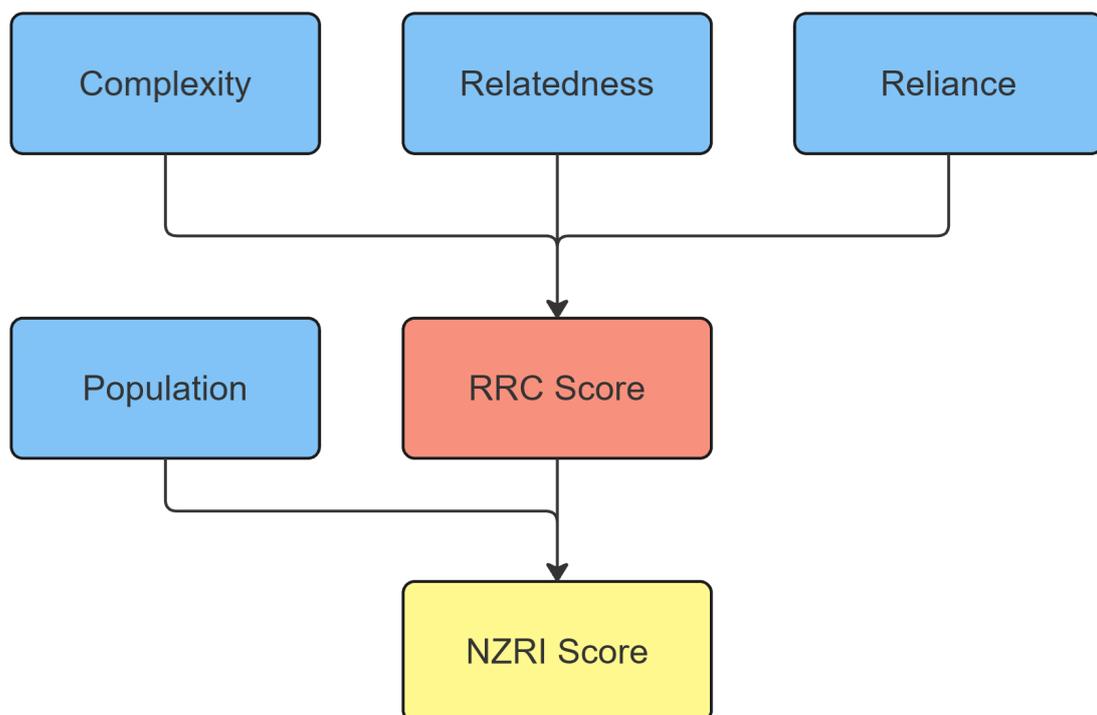
Complexity is a measure of the diversity of employment in an area. Economically complex areas, with varied industries, are presumed more resilient to economic shocks. Areas with many different types of industries and jobs are less affected (in the aggregate) to shocks in any one industry and have a greater range of skills that could be put to use in new or alternative industries. This analysis deploys the methodology outlined in the technical appendix of [Mealy and Coyle \(2019: 20\)](#) which uses employment data to measure complexity in LADs.

Relatedness is the extent to which industries are co-located, assuming that closely linked industries are more resilient due to the greater ease with which employees can reskill and transfer between sectors. This shows the relationships between different industries within the local authorities, providing insights into how industries cluster together geographically.

Working-Age Population in an area is factored in to capture the relative scale of risk in an area, using a similar approach as deployed by Fox et al. (2024) For example, some areas may be highly reliant on a vulnerable sector (e.g. agriculture) but employ relatively few people. Conversely, an area may have a mix of sectors, some vulnerable and some not, but with much larger numbers of potentially affected workers. Weighting risk by population draws on [approaches to modelling risks posed by natural hazards](#), which account for both vulnerability and exposure (i.e. size of population to be affected) to model overall risk.

These components are selected to understand the capacity of a local economy to bounce-back to an economic shock of workplace closure – and how easy it will be for individual workers to find alternative work in the same area.

Figure 1 - Core components of the Net Zero Vulnerability Index



Devising of the net zero resilience index

Using the above components, we calculated Location Quotients (LQ) using Equation 1:

$$LQ_{ij} = \frac{E_{ij}/\text{TotalEmpLocal}_i}{\text{TotalEmpIndustry}_j/\text{TotalEmpNational}}$$

E_{ij} is the number of employees in industry j within LAD i ; TotalEmpLocal_i is the total number of employees across all industries within LAD i ; $\text{TotalEmpIndustry}_j$ is the total number of employees in industry j across all LADs; and TotalEmpNational is the total number of employees across all industries and LADs (the entire country).

LQ values are binarized to create a binary matrix where the value is 1 if the LQ is greater than 1 and 0 otherwise. This matrix reflects the similarity between LADs based on the presence and concentration of industries, adjusted for the diversity of LADs and the ubiquity of industries.

This matrix is used in the calculation of an Economic Complexity Index (ECI) and a Product Complexity Index (PCI). The ECI measures the complexity of LADs based on the diversity and ubiquity of industries, while the PCI measures the complexity of industries based on their distribution across LADs.

The ECI is derived from the LAD similarity matrix S , which is constructed as:

$$S = D^{-1}MM^TD^{-1}$$

Where M is the binary matrix of LQ values, D is a diagonal matrix where $D_{ii} = \sum_j M_{ij}$, and M^T is the transpose of M . The ECI is then calculated as the eigenvector corresponding to the second largest eigenvalue of S :

$$\text{ECI} = v_2$$

Where v_2 is the eigenvector associated with the second largest eigenvalue of S . Similarly, the PCI is derived from the industry similarity matrix Q , which is constructed as:

$$Q = UM^TD^{-1}M$$

Where U is a diagonal matrix where $U_{jj} = \sum_i M_{ij}$. The PCI is calculated as the eigenvector corresponding to the second largest eigenvalue of Q :

$$\text{PCI} = w_2$$

Where w_2 is the eigenvector associated with the second largest eigenvalue of Q .

To calculate relatedness, a proximity matrix is constructed, measuring the relatedness between industries based on their co-occurrence in LADs. The proximity value between two industries is the minimum ratio of their joint presence to their individual presences. This matrix shows relationships and clustering between different industries within LADs, and is calculated using Equation 2, where for industries i and j , m_{ij} is the number of LADs where both industries are present, and m_i and m_j are counts for industries i and j .

$$\text{Proximity}_{ij} = \min\left(\frac{m_{ij}}{m_i}, \frac{m_{ij}}{m_j}\right)$$

Reliance values are calculated by first defining thresholds for 'overreliance' for both sector (all sectors) and subclass levels (only subclasses identified as at-risk) and identifying which industries meet these criteria in each LAD. In instances where multiple industries exceed these thresholds, values are summed to account for additional vulnerability. These values are then normalised. For the subclass level, this process is repeated for counts of employees. Over-reliant industries have these figures multiplied, which is again normalised, resulting in a final reliance score reflecting both employment magnitude and reliance.

These components are combined to form the final index. First, the Reliance-Relatedness (RR) score is calculated by matching reliant industries to their corresponding relatedness scores. In instances where more than once reliant industry is present in an LAD, a mean score is calculated, which is normalised. This is then multiplied with ECI scores (scaled between 0 and 1) to construct RRC scores, shown in Equation 3:

$$\begin{aligned} \text{RRC} = & \left(\text{ECI}^{\text{sector}} \times \text{Relatedness}^{\text{sector}} \times \text{Reliance}^{\text{sector}} \right) \\ & \times \left(\text{ECI}^{\text{subclass}} \times \text{Relatedness}^{\text{subclass}} \times \text{Reliance}^{\text{subclass}} \right) \end{aligned}$$

Controlling for working-age population exposure addresses the highest RRC scores, which result in an overrepresentation of rural communities deemed vulnerable, which typically have high employment rates in identified sectors (e.g., agriculture), but do not necessarily have high overall employment counts.

The resulting index allows us to map the geographies of vulnerability and resilience to net-zero as an economic shock in the UK. We do so across a geography of Local Authority Districts (LADs): a subregional division that provides the primary domain of local government in the UK. Our index includes 365 English, Welsh, and Scottish LADs. This geography also includes various (and emerging) geographies that can inform future net zero and green industrial strategy interventions in England, Wales and Scotland: such as geographies of devolved national governments and Combined Authorities. Comparable data for Northern Ireland are not available.

Further information

Key findings from the net-zero resilience index can be found [here](#)

Contact the researchers

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