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The geography of the disability employment gap: Exploring spatial variation in the relative employment rates of disabled people

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Abstract

The UK is one of the most spatially unequal countries in the developed world, and there is a long recognised need to 'level up' the economy. A strong case can be made to suggest that disabled people are particularly disadvantaged when living in a 'left behind' area and hence have the most to gain from levelling up. The disability employment gap, that is the difference between the employment rates of non-disabled people and disabled people, was 31 percentage points (pp) in Great Britain as a whole between 2014 and 2019 but ranged from 17pp to 43pp at local (ITL3) level. Using novel decomposition techniques we find that the key drivers of this spatial variation, each explaining similar shares, are local population characteristics and economic structure, including the level and nature of labour demand in geographical areas and the industry composition of the area. However, spatial variation in healthcare capacity, social capital, employer policies towards disability and the stringency of statutory welfare provision do not appear to have an effect on the gap. Our results suggest that locally adapted policies to narrow the gap may be more effective than a one-size-fits-all approach.

Keywords: disability employment gap, spatial inequalities

JEL classification: I14, J14, R12

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Declarations of interest: None

1. Introduction

The UK is one of the most spatially unequal countries in the developed world (HM Government, 2022). While some cities and regions are thriving economically, other areas are becoming increasingly 'left behind'. Much has been written about the need to ensure that national prosperity is distributed more equally across the country. In recent years, the government's strategy towards addressing spatial disparities has been described by the term 'levelling up'. While it is hoped that levelling up will benefit everyone living in a left behind area, it is possible that the process disproportionately affects people in certain demographic groups.

A strong case can be made to suggest that disabled people are particularly disadvantaged when living in a left behind area and hence have the most to gain from levelling up. Between 2014 and 2019, just under half (48%) of working age disabled people in Great Britain were employed, compared to about four-fifths (79%) of non-disabled people. Thus, the overall disability employment gap (DEG) in Great Britain was 31 percentage points (pp). Notably, however, there is substantial variation in the DEG across sub-regions ranging from 17pp in Buckinghamshire to 43pp in North Lanarkshire.[1] Our research shows that there is strong correlation between the size of these DEGs and levels of economic deprivation across areas.

In this paper, we make novel use of decomposition techniques to explore the reasons for this spatial variation in the DEG. By identifying the extent to which this variation is explained by differences in the demographic composition, we separate out the 'people effect' from the 'place effect' (defined as any remaining difference in the DEG once population characteristics are taken into account). We further unpack these place effects to explore the extent to which they can be explained by particular area-level characteristics.

Most of the existing literature in this area focuses on the supply side (i.e. the characteristics of disabled and non-disabled individuals). By taking a spatial approach, we are able to explore the role of demand-side factors. Our approach is most similar to Little (2009), who decomposes spatial variation in labour market inactivity due to long-term sickness and disability across the UK. However, we distinguish our

[1] Based on the authors' own calculations from the Annual Population Survey.

contribution by making two substantial extensions to this work. Firstly, while Little (2009) focuses on employment *levels*, we are concerned with employment *gaps*. This is a crucial distinction because it allows for individual and spatial level characteristics to affect the employment prospects of disabled people and non-disabled people differently. Secondly, while Little (2009) treats spatial variation above and beyond that explained by population characteristics as unexplained, we incorporate an important additional layer into our model to identify the impact of observable area-level characteristics. This addresses the fact that spatial variation in the DEG is, at least in part, attributable to measurable features of a local area, including factors related to demand, supply and policy. This is an aspect that has been neglected in most of the literature on disabled people's labour market outcomes.

We find that there are two key drivers of local variation in the DEG: the characteristics of the local population and observed area-level characteristics. These drivers each account for a standard deviation in the DEG of about 0.022 and 0.026 respectively (compared with an overall standard deviation of 0.053). A similar amount of variation (0.023) can also be attributed to unobserved area-level factors. Among the observed area-level characteristics, the DEG is particularly sensitive to the level and nature of labour demand, including the industry composition of the area. Spatial variation in healthcare capacity, social capital, employer policies towards disability and the stringency of statutory welfare provision do not appear to have a significant effect on the DEG.

2. Background and Literature

The last three decades have seen increased interest in using decomposition methods to understand disability gaps in labour market outcomes. The literature has primarily focused on the disability wage gap (Kidd et al., 2000; Thoursie, 2004; Baldwin and Marcus, 2007; Longhi et al., 2012) but also explores gaps in participation rates (Kidd et al., 2000), occupational distribution (Thoursie, 2004) and job loss (Mitra and Kruse, 2016), as well as the DEG itself (Jones, 2006). These studies identify the extent to which gaps can be explained by the relative characteristics of disabled and non-disabled people and whether any residual gaps are due to the differential treatment of disabled people or productivity deficits brought about by health impairments (Jones, 2006; Longhi et al., 2012). A recent contribution by Bryan et al. (2023) reviews this literature and identifies the extent to which the DEG can be explained by inequalities in educational attainment (see also Albinowski et al., 2023).

The majority of these studies focus on personal or household attributes; the role of local area characteristics is neglected. It is widely acknowledged that geography plays an important role in explaining labour market disadvantage and this is particularly true in the UK. The *Levelling Up* White Paper (HM Government, 2022) sets out the Government's priorities to level up economic prosperity across the country. According to the White Paper, the reasons for persistent geographic disparity are complex but include depletion of capital in 'left behind' areas, agglomeration effects attracting people and investment into already prosperous areas and the legacy of historical shocks such as deindustrialisation and the decline in domestic tourism. Economic variables such as productivity are highly spatially correlated with socioeconomic outcomes such as earnings, skills and health. Overman and Xu (2022) provide further analysis of these spatial disparities and conclude that much of the variation is explained by differences in the population characteristics of areas (particularly relating to education and skills) which may limit the efficacy of 'place-based policies'.

Healthy life expectancy at birth shows a high degree of geographic similarity to local productivity levels suggesting that, on average, population health is worse in areas with weak economic performance. This may be due to economic decline precipitating health problems (for example, due to the damaging effects of unemployment) or areas with historical concentrations of heavy industry being more likely to have a higher incidence of occupational ill-health (Beatty et al., 2000).

However, this correlation does not in itself explain spatial variation in the DEG. One would expect the spatial disparities highlighted in the White Paper to lead to reduced employment prospects for everyone living in left behind areas, so it is not immediately obvious why disabled people should be disproportionately affected. A possible explanation is provided by the existence of 'job queues' caused by labour market frictions that hold wages above their market clearing level.

Beatty et al. (2000) illustrate how health and disability may determine one's place in the job queue. All else being equal, people with health problems may be perceived as being less productive and will therefore be among the first to be made redundant and the last to be recruited. This is exacerbated by the fact that disabled people often have other characteristics that hinder employability, such as low levels of education. At any point in time job queues will vary in length across geographic areas due to spatial variation in labour market tightness. The longer the job queue, the higher the proportion of disabled people in that queue.

Even in situations where labour markets clear and job queues are minimal, disabled people may be less likely to be in work. Higher reservation wages (e.g. due to higher costs of living and eligibility for more generous out-of-work benefits) may lead disabled people to reject low wage offers and choose not to participate in the labour force. Reservation wages are more likely to be binding where there is downward pressure on wages, which again explains why the DEG may be wider in areas with a particularly slack labour market.

This theory also explains why the number of people claiming out-of-work benefits on the grounds of disability varies substantially across the country. Roberts and Taylor (2021) find that the propensity to claim disability benefits in the UK is not only determined by health status but is also significantly affected by local labour market conditions. Beatty and Fothergill (2023) identify the existence of 'hidden unemployment' where high levels of economic inactivity in certain areas reflect the lack of job opportunities, while Anyadike-Danes (2004, 2007) shows that people outside of the labour force due to sickness and disability make up a much larger share of the non-employed population in the north of England than in the south. Similar results have been found in Norway (Andersen et al., 2019) and the US (Coe et al., 2011; Charles et al., 2018). Variations in labour market demand also affect the DEG directly. In the US, Kruse and Schur (2003) find that the employment rate of disabled people is more sensitive to state-level unemployment rates than the employment rate of non-disabled people.

The literature identifies several other area-level factors, aside from labour market demand, that might be expected to influence the DEG. Studies by Agovino and Rapposelli (2014, 2017) focus on how disability employment policy and legislation are implemented across provinces in Italy, while Maroto and Pettinicchio (2014b) explore the effects of state-level variation in the interpretation and enforcement of the Americans with Disabilities Act. While equality laws are applied and enforced nationally in the UK, we may expect to see some spatial variation due to how employment law is interpreted and applied differently across employers and sectors.

Some studies have investigated the relative effects of a range of spatial factors on the participation and employment of disabled people. Botticello et al. (2012) find that area-level indicators of socio-economic status and urbanicity (percentage of the population living in an urban area) were more predictive of employment for people with spinal cord injury than local unemployment rates in the US.

Also using US data, Sevak et al. (2018) find that state and county level disability employment rates are associated with local economic conditions (poverty rate, unemployment rate, participation rate and blue-collar rate) and the physical environment (population density, public transport, number of physicians and violent crime) but have no relationship with state or local policies. Zhou et al. (2019) find that spatial variation in the labour force participation rate of disabled people across Australia is explained by median weekly income, local employment rates, labour market demand, disability prevalence and educational levels among disabled people. The findings of these studies indicate that area level characteristics might be affecting the supply side of the labour market as well as the demand side.

To our knowledge the only study to apply decomposition methods to spatial variation in disability employment (or, more specifically, levels of inactivity due to long-term sickness or disability) is Little (2009). He finds that demographic differences explain only a small fraction of spatial variation, hinting at the importance of area-level factors (for example variation in employment opportunities).

3. Method

Our method extends the standard Oaxaca (1973) decomposition of the difference in the mean outcomes of two groups to allow for variation in the difference across spatial units. In our case, the mean outcome is the employment rate, the two groups are disabled and non-disabled people, and the spatial unit is the local area (as defined in Section 5). Using this method, we can take the DEG in a given area and assess why it differs from the national DEG (or alternatively another local DEG), decomposing the difference into the components due to local population characteristics (people effects), and observed and unobserved area characteristics (place effects). Our extension is related to other methods that seek to explain mean differences over time (see Kim, 2010, for an analysis of changes in the racial wage gap and Kröger and Hartmann, 2021, for a methodological review). As emphasised by Kröger and Hartmann (2021), there are numerous possible decompositions, each with its own substantive interpretation. Accordingly, and given the spatial context, our method differs significantly from these decompositions.[2]

[2] Our method also differs from a variance decomposition developed to explain spatial differences in outcomes such as earnings (Gibbons et al, 2014, further applied in Overman and Xu, 2022). While this technique is appropriate for analysing the spatial variance of outcomes measured at the individual level, it is not applicable to mean differences between groups.

We start with an employment model represented by equation (1), where the index $D \in (0,1)$ denotes the parameters for non-disabled and disabled people respectively.

$$y_{ij}^{D} = \beta_0^{D} + \mathbf{x}_{ij}^{D}\boldsymbol{\beta}^{D} + \mathbf{z}_j\boldsymbol{\gamma}^{D} + u_j^{D} + \varepsilon_{ij}^{D} \tag{1}$$

For each individual i living in area j, $y_{ij} \in (0,1)$ denotes whether they are in employment. The vector $\mathbf{x}_{ij}^{D}$ contains all other individual and household level characteristics, $\mathbf{z}_j$ is a vector of local area characteristics and $\boldsymbol{\gamma}^{D}$ denotes the extent to which each element in $\mathbf{z}_j$ affects the employment rate of non-disabled and disabled people respectively in area j. The term u_j^{D} captures any unobserved area level effects, while ε_{ij}^{D} is the remaining residual. Equation (1) has a two-level structure and so the use of ordinary least squares (OLS), which ignores the area effect u_j^{D}, would not be appropriate. We could specify u_j^{D} as a random effect and estimate the model by generalised least squares, but to obtain unbiased coefficient estimates we would require u_j^{D} to be uncorrelated with the regressors. This condition is unlikely to hold; for instance, average levels of observed education may be correlated with unobserved local economic factors that affect employment. In addition, we wish to clearly separate the variation in employment (and hence the DEG) within areas from the variation between areas. This will also enable us to conduct exploratory data analysis of the between variation.

To address these issues, we estimate the within and between area components of the model in separate steps.[3] We first estimate the within area model:

$$y_{ij}^{D} = \mathbf{x}_{ij}^{D}\boldsymbol{\beta}^{D} + \nu_j^{D} + \varepsilon_{ij}^{D} \tag{2}$$

where ν_j^{D} is an area fixed effect (AFE) that includes both observed and unobserved area characteristics ($\nu_j^{D} = \beta_0^{D} + \mathbf{z}_j\boldsymbol{\gamma}^{D} + u_j^{D}$ from equation (1)). Applying OLS to equation (2), we obtain coefficient

[3] For discussion of a similar two-step approach in other contexts, see for example Card (1995), Donald and Lang (2007) and Kedar and Shively (2005).

estimates in $\widehat{\boldsymbol{\beta}}^D$ and an estimate of the AFE denoted by $\hat{v}_j^D$ which can be seen as the local employment rate adjusted for the effects of individual and household characteristics in the area.

In the second step, we estimate the between area model by regressing the estimated AFE on observable area level factors $\mathbf{z}_j$:

$$\hat{v}_j^D = \beta_0^D + \mathbf{z}_j \boldsymbol{\gamma}^D + \eta_j^D \tag{3}$$

where η_j^D is a residual (and $\eta_j^D = u_j^D + (\hat{v}_j^D - v_j^D)$, i.e. it differs from u_j^D in equation (1) because it includes the estimation error associated with $\hat{v}_j^D$). This step yields estimates $\hat{\beta}_0^D$ and $\hat{\boldsymbol{\gamma}}^D$ (derived using weighted least squares).[4]

Using the coefficient estimates from these two steps, we can derive the DEG decomposition from equation (2). Since the OLS residuals $\hat{\varepsilon}_{ij}^D$ sum to zero within areas, the local employment rate can be expressed as:

$$\bar{y}_j^D = \hat{\beta}_0^D + \bar{\mathbf{x}}_j^D \widehat{\boldsymbol{\beta}}^D + \mathbf{z}_j \hat{\boldsymbol{\gamma}}^D + \hat{\eta}_j^D \tag{4}$$

where $\bar{y}_j$ denotes the mean of y within area j and similarly for $\bar{\mathbf{x}}_j$. And the overall employment rate is:

$$\bar{\bar{y}}^D = \hat{\beta}_0^D + \bar{\bar{\mathbf{x}}}^D \widehat{\boldsymbol{\beta}}^D + \bar{\bar{\mathbf{z}}}^D \hat{\boldsymbol{\gamma}}^D + \overline{\overline{\hat{\eta}_J^D}} \tag{5}$$

[4] The residual η_j^D is likely to be heteroskedastic with a variance of $\sigma^2 + \omega_j^2$ where $\sigma^2 = var(u_j^D)$ and $\omega_j^2 = var(\hat{v}_j^D - v_j^D)$. As such, OLS estimation of equation (3) is inconsistent (although unbiased) and yields inconsistent standard errors. Following Lewis and Linzer (2005), we estimate equation (3) using weighted least squares where the weight $w_j = \frac{1}{\sqrt{\hat{\sigma}^2 + \widehat{\omega}_j^2}}$. Here, $\widehat{\omega}_j^2$ is estimated from equation (2) and $\hat{\sigma}^2 = \frac{\sum_{j=1}^{J} \hat{\eta}_j^2 - \sum_{j=1}^{J} \widehat{\omega}_j^2 + tr[(\mathbf{Z}'\mathbf{Z})^{-1}\mathbf{Z}^i\mathbf{G}\mathbf{Z}]}{J-k}$ where J is the number of areas, k is the number of area level characteristics, $\sum_{j=1}^{J} \hat{\eta}_j^2$ is the sum of squared residuals from an OLS estimation of equation (3), $\mathbf{Z}$ is a $J \times (k+1)$ matrix containing the area characteristics and the constant and $\mathbf{G}$ is a $J \times J$ diagonal matrix with $\widehat{\omega}_j^2$ as the jth diagonal element. Equation (3) is estimated separately for the disabled and non-disabled groups, with a separate set of weights, but the D superscripts have been removed in this notation for simplicity.

where $\bar{\bar{y}}$ denotes the overall (grand) mean of y and similarly for $\bar{\bar{\mathbf{x}}}$, $\bar{\bar{\mathbf{z}}}$ and $\bar{\bar{\hat{\eta}}}_j$. The last term $\overline{\overline{\hat{\eta}_j^D}}$ arises because of differences in the sample size in local areas (it is the average of the local area effects weighted by the area sample sizes). With equally sized areas, the estimated area effects $\hat{\eta}_j^D$ would sum to zero over the sample of individuals because, at the area level, they are symmetric around $\hat{\beta}_0^D$. Note also that, unlike at the area level, $\bar{\bar{\mathbf{z}}}^D$ differs for disabled and non-disabled people because they are not equally distributed across areas.

The local DEG is:

$$DEG_j = \bar{y}_j^0 - \bar{y}_j^1 = (\hat{\beta}_0^0 - \hat{\beta}_0^1) + (\bar{\mathbf{x}}_j^0\hat{\boldsymbol{\beta}}^0 - \bar{\mathbf{x}}_j^1\hat{\boldsymbol{\beta}}^1) + (\mathbf{z}_j\hat{\boldsymbol{\gamma}}^0 - \mathbf{z}_j\hat{\boldsymbol{\gamma}}^1) + (\hat{\eta}_j^0 - \hat{\eta}_j^1) \tag{6}$$

And the overall DEG is:

$$DEG = \bar{\bar{y}}^0 - \bar{\bar{y}}^1 = (\hat{\beta}_0^0 - \hat{\beta}_0^1) + (\bar{\bar{\mathbf{x}}}^0\hat{\boldsymbol{\beta}}^0 - \bar{\bar{\mathbf{x}}}^1\hat{\boldsymbol{\beta}}^1) + (\bar{\bar{\mathbf{z}}}^0\hat{\boldsymbol{\gamma}}^0 - \bar{\bar{\mathbf{z}}}^1\hat{\boldsymbol{\gamma}}^1) + (\overline{\overline{\hat{\eta}_j^0}} - \overline{\overline{\hat{\eta}_j^1}}) \tag{7}$$

Hence the difference between the local and overall DEG is:

$$\begin{aligned} DEG_j - DEG = {} & \left(\bar{\mathbf{x}}_j^0 - \bar{\bar{\mathbf{x}}}^0\right)\hat{\boldsymbol{\beta}}^0 - \left(\bar{\mathbf{x}}_j^1 - \bar{\bar{\mathbf{x}}}^1\right)\hat{\boldsymbol{\beta}}^1 + \left(\mathbf{z}_j - \bar{\bar{\mathbf{z}}}^0\right)\hat{\boldsymbol{\gamma}}^0 - \left(\mathbf{z}_j - \bar{\bar{\mathbf{z}}}^1\right)\hat{\boldsymbol{\gamma}}^1 \\ & + \left(\hat{\eta}_j^0 - \hat{\eta}_j^1\right) - (\overline{\overline{\hat{\eta}_j^0}} - \overline{\overline{\hat{\eta}_j^1}}) \end{aligned} \tag{8}$$

This can be written as:

$$DEG_j - DEG = \Delta\bar{\mathbf{x}}_j^0\hat{\boldsymbol{\beta}}^0 - \Delta\bar{\mathbf{x}}_j^1\hat{\boldsymbol{\beta}}^1 + \Delta\mathbf{z}_j^0\hat{\boldsymbol{\gamma}}^0 - \Delta\mathbf{z}_j^1\hat{\boldsymbol{\gamma}}^1 + \left(\hat{\eta}_j^0 - \hat{\eta}_j^1\right) - (\overline{\overline{\hat{\eta}_j^0}} - \overline{\overline{\hat{\eta}_j^1}}) \tag{9}$$

Here the Δ notation denotes the difference between (mean) local characteristics and overall mean characteristics. Applying an Oaxaca (1973) decomposition:

$$\begin{aligned} DEG_j - DEG = {} & \left(\Delta\bar{\mathbf{x}}_j^0 - \Delta\bar{\mathbf{x}}_j^1\right)\hat{\boldsymbol{\beta}}^0 + \Delta\bar{\mathbf{x}}_j^1\left(\hat{\boldsymbol{\beta}}^0 - \hat{\boldsymbol{\beta}}^1\right) + (\bar{\bar{\mathbf{z}}}^1 - \bar{\bar{\mathbf{z}}}^0)\hat{\boldsymbol{\gamma}}^0 + \Delta\mathbf{z}_j^1(\hat{\boldsymbol{\gamma}}^0 - \hat{\boldsymbol{\gamma}}^1) \\ & + \left(\hat{\eta}_j^0 - \hat{\eta}_j^1\right) - (\overline{\overline{\hat{\eta}_j^0}} - \overline{\overline{\hat{\eta}_j^1}}) \end{aligned} \tag{10}$$

This can be simplified as:

$$DEG_j - DEG = \left(\Delta\bar{\mathbf{x}}_j^0 - \Delta\bar{\mathbf{x}}_j^1\right)\widehat{\boldsymbol{\beta}}^0 + \Delta\bar{\mathbf{x}}_j^1\left(\widehat{\boldsymbol{\beta}}^0 - \widehat{\boldsymbol{\beta}}^1\right) + \Delta\mathbf{z}_j^1(\widehat{\boldsymbol{\gamma}}^0 - \widehat{\boldsymbol{\gamma}}^1) + \left(\hat{\eta}_j^0 - \hat{\eta}_j^1\right) + c \tag{11}$$

where $c = (\bar{\bar{\mathbf{z}}}^1 - \bar{\bar{\mathbf{z}}}^0)\widehat{\boldsymbol{\gamma}}^0 - (\overline{\overline{\hat{\eta}_j^0}} - \overline{\overline{\hat{\eta}_j^1}})$ and is a constant term not variant in j.

The first term on the right-hand side of equation (11) shows how much of the local difference is due to individual characteristics, specifically how much the gap in characteristics between disabled and non-disabled people differs from the overall average. In other words, are disabled and non-disabled people more different from each other locally than they are nationally? We call this the component due to *relative* individual characteristics. The second term shows how much of the difference is because there is a local concentration of characteristics that are differentially rewarded or penalised. For example, there could be more people with degrees or no qualifications than nationally, which will disproportionately affect disabled people's employment (Bryan et al., 2023). We call this the component due to *absolute* individual characteristics. The third term shows how much of the difference is because the local area has observable characteristics that disproportionately reward or penalise disabled people's employment. The fourth term is the difference in unobservable local area effects, while the fifth term is a constant which is the same for all areas.

We can also use the decomposition to make a direct comparison of two local areas. It follows from equation (11) that the difference between the DEG in area j and area k can be expressed as:

$$DEG_j - DEG_k = \left[\left(\bar{\mathbf{x}}_j^0 - \bar{\mathbf{x}}_j^1\right) - (\bar{\mathbf{x}}_k^0 - \bar{\mathbf{x}}_k^1)\right]\widehat{\boldsymbol{\beta}}^0 + \left(\bar{\mathbf{x}}_j^1 - \bar{\mathbf{x}}_k^1\right)\left(\widehat{\boldsymbol{\beta}}^0 - \widehat{\boldsymbol{\beta}}^1\right) + \left(\mathbf{z}_j^1 - \mathbf{z}_k^1\right)(\widehat{\boldsymbol{\gamma}}^0 - \widehat{\boldsymbol{\gamma}}^1) + \left(\hat{\eta}_j^0 - \hat{\eta}_j^1\right) - (\hat{\eta}_k^0 - \hat{\eta}_k^1) \tag{12}$$

The first term is the component arising because the *relative* characteristics of disabled and non-disabled people differ between the areas, while the second term is the component due to differences in *absolute* individual characteristics. The third term is the contribution of differences in the observed characteristics of the two areas, and the fourth term is the difference in unobservable local area effects. The constant from the previous decomposition drops out now that we are comparing the areas directly and not relative to an overall mean.

4. Spatial variables

A novel aspect of our approach is to measure some of the area level effects through observable variables, contained in the vector $\mathbf{z}_j$. To select these variables, we first undertook a thorough review of the literature to understand the factors that might be expected to explain spatial variation in the DEG and then scoped the available data to measure these factors at a sub-regional level in Great Britain. We classified the factors into three broad groups: demand, supply and policy. Here we discuss the rationale for including these factors, and Appendix 1 then provides more detail on the measures that we use.

4.1 Demand

The DEG is in part determined by the relative demand for disabled and non-disabled people in the labour market. As most people work or seek work close to where they live, we would expect variation in local labour market demand to be an important factor in explaining spatial variation in the DEG. This level of demand can be captured by measuring local unemployment rates.

One could argue that the contemporaneous unemployment rate is an outcome variable rather than an exogenous indicator of labour demand. In the context of explaining the DEG, however, unemployment is an appropriate measure for two reasons. First, we are considering the effects of unemployment on the gap in employment rates, not the employment rates themselves. If unemployment influenced the employment rates of the two groups equally, there would be no effect on the DEG. Second, the vast majority of non-employed people are economically inactive and therefore are not numbered among the unemployed. However, the decision to participate may be influenced by perceptions about the availability of jobs locally which in turn is related closely to the unemployment rate.

As well as the level of demand in the local economy, it is also possible that the DEG may be influenced by the composition of that demand. Maroto and Pettinicchio (2014a) find that disabled people in the US are disproportionately segregated into low-skilled and low-paid occupations while Agovino and Rapposelli (2012) find that Italian regions with a strong private sector are more effective at employing disabled people. We proxy for this using local gross value added (GVA) per hour worked as an indicator of average local productivity. We also consider the share of employed population working in each industry sector and occupation level. Since there is geographic variation in the concentration of industries and jobs (leading to different levels of productivity), these measures broadly capture how the type of employment demand varies between areas.

In a supplementary analysis, we also measure the concentration of jobs in an area by the extent to which they are suitable for homeworking, provide flexibility for workers and allow workers to exercise autonomy in their work. There is some evidence to suggest that working from home can improve the employment prospects of disabled people (Edwards and Field-Hendrey, 2002) but this finding is questioned by more recent evidence showing that disabled people are less likely to work from home and do not disproportionately benefit from doing so (Hoque and Bacon, 2021). There is also evidence that access to flexible working (Anand and Sevak, 2017) and allowing workers more discretion over how to perform their work tasks (Jones and Sloane, 2010) can reduce employment barriers for disabled people.

4.2 Supply

Unlike labour demand, the supply of labour is largely determined at the individual level. This includes the demographic characteristics and human capital endowments of the working age population. As such, these supply-side factors are incorporated into $\mathbf{x}_{ij}^{D}$. However, there may also be area level characteristics with the potential to enhance the employability of disabled people. One such factor is the relative supply of health care across different geographic areas. Unmet need for healthcare is found to be a barrier to employment for disabled people (Gettens and Henry, 2015). Therefore, disabled people living in areas with strong healthcare provision may be more advantaged. We measure this healthcare capacity by estimating the number of general practitioners (GPs) per thousand population in each area.

Another supply-side factor that exists beyond the level of the individual is social capital. This captures (among other things) the extent to which institutions and social norms in an area support people to participate in the labour market and access employment. It is known that strong social networks can be an important factor in enabling disabled people to access employment (Potts, 2005; Langford et al., 2013; Kuiper et al., 2016). We measure social capital using the Social Fabric Index (Tanner et al., 2020).

In a supplementary analysis for England only (due to the unavailability of comparable data for Scotland and Wales), we also measure the quality of public transport in an area. We estimate the average journey times from home to the nearest large employment centre using public transport, both in absolute terms and relative to making the same journey by car.[5] Evidence on the effects of transportation on the employment of disabled people is sparse. While many disabled people cite lack of transport as a barrier to employment (Anand and Sevak, 2017), availability of public transport is found not to influence employment outcomes (Farber and Paez, 2010).

4.3 Policy

Finally, spatial differences in the DEG may be influenced by policy. Of course, much policy is implemented at a national level and local administrations have limited powers to develop specific policies related to the employment of disabled people; for example, the Equality Act applies to all firms in Great Britain. In contrast, Disability Confident is a voluntary initiative that was introduced by the UK government to encourage employers to adopt inclusive practices for employing disabled people, and to change attitudes towards disability.[6] The results of a Department for Work and Pensions (2018a) survey suggest that it has been successful in both aims. We exploit spatial differences in the take-up of this scheme to assess whether this has any bearing on the DEG.

An important factor that is likely to affect the decision to participate in the labour market, particularly for disabled people, is the attractiveness of out-of-work welfare benefits and the ease by which these can be accessed. There is a very large literature on this subject (e.g. Banks et al., 2015; Milligan and Schirle, 2019; Garcia-Mendico et al., 2020; Muller and Boes, 2020). Benefit levels for disabled people unable to work (administered through the Employment Support Allowance and Universal Credit) are set nationally and do not vary by area or even country within the UK. However, due to spatial variation in wages, the relative returns to non-participation in the labour market do vary. We expect that this

[5] Note that these journey time indicators do not capture the accessibility of public transport (for example, cost or frequency of service) which may be more important factors to enable disabled people to access employment.
[6] www.disabilityconfident.campaign.gov.uk

variation is already captured in our demand measures, so we do not include an additional measure relating to benefit levels. Nevertheless, there is evidence of a certain degree of spatial variation in the 'strictness' of local administration of these welfare and employment support programmes. To account for this, we observe the number of sanctions applied as a proportion of the Universal Credit caseload in each local area. High sanction rates would indicate both a more stringent approach to conditionality and a greater willingness to enforce that conditionality.

5. Data

Our main data source is the Annual Population Survey (APS), produced by the Office for National Statistics (2022a).[7] This is a large cross-sectional dataset containing a representative sample of households and individuals from across the UK each year.[8] We pool six years of data covering the period 2014 to 2019[9] and retain all working age people (16-64)[10] for the analysis. Our sample consists of 195,455 disabled people and 791,401 non-disabled people.

The spatial geography of interest for this study is International Territorial Level 3 (ITL3, formerly NUTS3).[11] There are 166 ITL3 regions in Great Britain (England, Wales and Scotland).[12] These ITL3 areas map on to local authority boundaries such that some are composed of a single local authority while others are aggregations of two or more local authorities. Sample sizes for individual areas range from 830 to 32,329 and the mean sample size is 5,945.

[7] In order to access a comprehensive set of variables (including detailed information about health conditions and area of residence), we use the Secure Access version of the APS. Secure access to the APS is via the UK Data Service Secure Lab https://ukdataservice.ac.uk/help/secure-lab/what-is-securelab/

[8] Due to some inconsistencies in the availability of spatial data, individuals living in Northern Ireland are excluded from our sample. The areas of Orkney and Shetland are also excluded due to small sample sizes.

[9] This covers the period from the first year where disability is defined in the APS according to the Equality Act definition (2014) to the last year before the global pandemic (2019).

[10] This age range is chosen as it matches the working population age range used by the UK Government to measure the DEG.

[11] We note that these are administrative areas and do not necessarily reflect local economic geographies. An alternative approach would be to divide the country into travel to work areas (see Overman and Xu, 2022) but this would be challenging for our analysis due to widely differing populations (and hence small sample sizes in some areas) and difficulties in converting many of our area-level data into non-administrative spatial units. Our approach of using geographies based on local government boundaries is in line with other relevant UK papers including Little (2009) and Beatty and Fothergill (2023).

[12] Excluding Orkney and Shetland as explained above.

Our dependent variable y_i is employment status, which is based on the International Labour Organization (ILO) definition of basic economic activity. It is a dummy variable equal to 1 if the individual is employed (including self-employed) and 0 if they are not employed (either ILO unemployed or economically inactive).

Our 'treatment' variable D_i is disability. Disability is defined according to the Equality Act (2010). A person is deemed to be disabled ($D_i = 1$) if they report having any health problems or illnesses lasting 12 months or more and say that this reduces their ability to carry out day-to-day activities. They are otherwise classified as non-disabled ($D_i = 0$).

We also control for a number of other characteristics that make up $\mathbf{x}_i$. Details of these measures are tabulated in Appendix 1. The variables included in $\mathbf{z}_j$ come from other sources and are merged into the main APS dataset at an ITL3 level. Details of these measures, including data sources, are also tabulated in Appendix 1.

6. Results

The overall DEG in Great Britain across the years 2014-2019 was 31pp. There was, however, a large distribution in DEGs across ITL3 areas, from 17pp in Buckinghamshire to 43pp in North Lanarkshire. The full distribution by region is shown in Figure 1, from which it is clear that while there are differences in the DEG between regions (the North East and Scotland have larger DEGs than the South East, for example), these are dwarfed by the differences between ITL3 areas within regions.

In the rest of this section, we document the separate steps of the analysis as follows. First, we estimate employment equations for the non-disabled and disabled populations respectively, generating AFEs for each area (equation (2)). Second, we plot the correlation between these AFEs and a set of area level characteristics and estimate multivariate regressions to assess the importance of each of these characteristics to the spatial variation in employment rates (equation (3)). Third, we use the coefficients from these two stages to decompose the difference between each area's DEG and the national DEG (equation (11)). Using tables, charts and maps we illustrate various features of the decompositions. We begin with a simple comparison of population characteristics and residual area effects, and then move on to find the specific area level characteristics that explain spatial variation in the DEG. We also decompose the difference in the DEGs of two example areas (equation (12)). Fourth, we briefly summarise the results of supplementary decomposition analysis based on a different set of area-level characteristics.

6.1 Employment rates

We start by estimating equation (2) for the non-disabled and disabled populations respectively to find the estimated coefficient vectors $\widehat{\boldsymbol{\beta}}^{\mathbf{0}}$ and $\widehat{\boldsymbol{\beta}}^{\mathbf{1}}$. These are tabulated in Appendix 2. At the same time, for each ITL3 area we estimate the AFEs $\hat{v}_j^{\mathbf{0}}$ and $\hat{v}_j^{\mathbf{1}}$. These AFEs denote the extent to which the employment rate of non-disabled and disabled people respectively is above or below the level it would be expected to be given the population characteristics of the area.

As a first step in understanding how these AFEs may be explained by specific area-level characteristics, we present a series of bivariate scatter plots. These are shown in Figures 2 through to 15. In each graph, the orange line shows the correlation with the AFEs from the employment equation for disabled people, while the blue line shows the correlation with the AFEs from the employment equation for non-disabled people.

On the demand side, we see that higher AFEs for disabled people are associated with lower unemployment rates (Figure 2), higher levels of GVA per hour worked (Figure 3), a higher proportion of the employed population working in knowledge services (Figure 4, comparing to Figures 5 to 7) and a higher proportion of the employed population working in more high-skilled occupations (Figures 8 to 11). On the supply side, the correlation with GPs per head is negligible (Figure 12) while there is a positive association between AFEs for disabled people and levels of social capital, as measured by the Social Fabric Index (Figure 13). In terms of policy variables, somewhat counterintuitively we find that the AFEs for disabled people are negatively associated with both the concentration of Disability Confident employers (Figure 14) and the strictness of the benefit system (Figure 15). In most of the scatter plots, the correlations for non-disabled people are relatively flat, indicating that these area-level characteristics matter more for the employment prospects of disabled people than non-disabled people.

Overall, these correlations indicate that it is demand-side factors (GVA, industry and occupational composition) that are the strongest predictors of area level employment rates, and in particular of the divergence of rates between disabled and non-disabled people. Supply and policy differences are much more muted as discriminators. This does not mean that supply and policy factors do not have a causal effect on employment, just that these factors are not what explains the observed differences in employment rates across areas. It could also be that the various characteristics are correlated with each other. To account for this, we next move to a multivariate analysis of the area level effects.

Appendix 3 shows the estimated coefficient vectors $\hat{\boldsymbol{\gamma}}^{\mathbf{0}}$ and $\hat{\boldsymbol{\gamma}}^{\mathbf{1}}$ from equation (3) where $\mathbf{z}_j$ is a vector of all the area characteristics. We can see that, after controlling for all other area level characteristics, unemployment continues to be significantly downward sloping against the AFEs in both equations, but with a larger negative coefficient for disabled people (consistent with Figure 2).

In both equations, significant upward slopes are observed for the proportion of people employed in knowledge services but the coefficient for disabled people is more than three times the size of the coefficient for non-disabled people. Manufacturing employment is also positively associated with the employment rate of both disabled and non-disabled people.

The coefficients pertaining to the concentration of different occupation levels contrast markedly with the bivariate correlations shown in Figures 8 to 11. Relative to Level 1 occupations, a higher concentration of Level 4 occupations is associated with lower employment rates for both groups, with the coefficient over twice as large for disabled people. The Level 2 and Level 3 coefficients are also negative and significant for disabled people. This reversal in the relative slopes can be attributed to the fact that occupational mix is likely to be highly correlated with other variables in the model, such as industry mix. The results suggest that, given an area is economically thriving (for example, in terms of low unemployment and a thriving knowledge sector), disabled people benefit more from there being a larger number of lower skilled jobs (particularly elementary occupations); this is because disabled people are disproportionately employed in lower skilled occupations.

It is notable that GVA is no longer a significant factor for either group. Thus, while areas with high GVA have higher employment of disabled people (Figure 3), this appears to be because of their industry (and occupation) mix.

Regarding supply side variables, the Social Fabric Index is not a significant factor after controlling for other area level measures. However, the coefficient for GPs per head continues to be negative for disabled people. In terms of policy variables, Universal Credit sanction rates are negatively associated with the employment rate of disabled people but there is no effect for non-disabled people. The coefficient for Disability Confident is negative for both groups but not significant.

6.2 Decomposing the DEGs

To assess the relative importance of area level factors and population characteristics in explaining spatial variation in the DEG, we now proceed to decompose the difference between each area's DEG and the national DEG according to the decomposition set out in equation (11).

6.2.1 Comparing population characteristics and area effects

We begin by simply splitting the DEG difference into two components: the portion explained by population characteristics, incorporating the first two terms on the right hand side of equation (11); and the remaining area level component, incorporating the last three terms.

In Figure 16, we plot the overall difference from the national DEG against the difference explained by population characteristics. Where an area sits on the 45-degree line, its DEG difference is completely explained by population characteristics. For example, Cornwall and Isles of Scilly (in South West England) has a DEG about 3pp lower than the national average. However, being positioned as it is very close to the line, virtually all of this difference is explained by the extent to which the working age population of Cornwall and Isles of Scilly is different to that of Great Britain. If the population of Cornwall and Isles of Scilly had the same characteristics as the national average then the model predicts that it would also have almost the same DEG.

If an area does not sit on the 45-degree line, its DEG difference is not fully explained by population characteristics; that is there is an additional effect on the DEG due to area level factors. It follows that this area effect[13] is quantified by the horizontal distance from the 45-degree line in Figure 16 to each data point. All areas to the left of the 45-degree line are places that have a smaller DEG than is explained by individual characteristics (a negative area effect). This group mainly includes places like Berkshire (in South East England) that have a smaller DEG than nationally but only part of this difference is explained by how the population is different to the national average based on its observed characteristics. Places like Haringey and Islington (in London), on the other hand, have a larger DEG than nationally but this would be larger still if explained purely by the characteristics of the local population. These areas are 'over-performing' in the sense that they benefit from favourable area effects.

Similarly, all areas to the right of the 45-degree line are places that have a larger DEG than is explained by individual characteristics (a positive area effect). Places like Gwent Valleys (in Wales) have a larger DEG than nationally but population characteristics explain only part of this difference. Staffordshire (in the West Midlands region of England) is an example of a place where population characteristics predict the DEG difference to be even more negative than it actually is. These areas can be thought of as 'under-performing'.

We can map the information in Figure 16 to show how different areas compare before and after we account for population characteristics. The maps in Figure 17 show the spatial distribution of the actual DEG differences and the adjusted DEG differences (horizontal distances from the 45-degree line in Figure 16) respectively. The left map shows the quintile distribution of the raw DEG differences, where red areas have the largest DEGs (most positive DEG differences) and the dark green areas have the lowest DEGs (most negative DEG differences). The right map shows how this quintile distribution changes when we account for population characteristics and hence 'reveal' the role played by area factors. Again, the red areas are in the quintile with the most positive area effects (DEGs higher than what would be expected based on population characteristics) and the dark green areas are in the quintile with the most negative area effects (DEGs lower than what would be expected

[13] We define the 'area effect' as the component of the DEG explained by area effects (as opposed to population characteristics). This is distinct from the term 'area fixed effect' (AFE) which refers to the estimated fixed effects from the two (disabled and non-disabled) employment equations.

based on population characteristics). 'Over-performing' areas tend to be concentrated in southern England, while the worst 'under-performers' are in parts of northern England, Wales and Scotland. The overall pattern is similar to the distribution of actual DEGs but there are also some clear differences. For example, some rural areas of northern Scotland and mid-Wales move into a higher quintile (i.e. become 'more red') once population characteristics are taken into account while several areas in London (less easy to see on the map) move into a lower quintile (i.e. become 'more green').

The portion of the DEG difference attributable to differences in individual characteristics can itself be decomposed into two parts, and this is illustrated in Figure 18 to compare the DEGs of the ITL3 areas containing the ten Core Cities in Great Britain (OECD, 2020). The blue segment (relative characteristics) corresponds to the first term on the right-hand side of equation (11) and denotes the extent to which the local DEG is explained by how the disabled and non-disabled population are characteristically different from each other in a way that differs from the relative composition of the two groups nationally. The orange segment (absolute characteristics) corresponds to the second term on the right-hand side of equation (11) and denotes the extent to which the local DEG is explained by how the disabled population is characteristically different to the national average. The grey segment shows the residual area level effect.

Figure 18 shows that, in most of the core cities (Birmingham and Leeds being the exceptions), absolute characteristics explain more of the DEG than relative characteristics. This is perhaps unsurprising as areas are likely to be more different to each other in the overall characteristics of the population than in the difference between the characteristics of the disabled and non-disabled populations. The area level effects indicate that Glasgow City, Cardiff and Vale of Glamorgan, Liverpool, Manchester and Tyneside are all 'under-performing' cities. The population characteristics of Glasgow, Liverpool, Manchester and Tyneside are such that we would expect them to have an above average DEG, and yet their actual DEG is even higher. On the other hand, Cardiff would be expected to have a below average DEG but actually has a DEG closer to the Great Britain average. In contrast, Bristol, Birmingham, Nottingham, Leeds and Sheffield are 'over-performing' cities. All five cities would be expected to have lower than average DEGs based on their population characteristics, but their actual DEGs are even lower than expected.

6.2.2 Explaining the area affects

We now seek to explain these area effects further by incorporating area level characteristics, and reporting a detailed decomposition of the third term of equation (11). Figure 19 shows a graphical representation of this decomposition for the ten core cities (extending the decomposition of Figure 18 that included population characteristics only).

The figure shows that including area level characteristics goes some way to explaining the area effects but in some cities the remaining residual (unexplained by both individual and area level characteristics) continues to be high. In Cardiff, Birmingham, Sheffield, Manchester and Tyneside, the residual is larger than it was before we added the area level variables (Figure 18), due to the net effect of the area characteristics predicting the DEG difference to be the opposite direction to what it actually is. In contrast, the residual is very close to zero for Glasgow City and Liverpool, suggesting that the mix of individual and area level variables used in the model predict quite well the actual DEG in these two cities.

Among the Core Cities, the area characteristics that appear to be most important are industry composition (e.g. in Bristol) and occupational composition (e.g. in Nottingham). As is clear from equation (11), these contributions reflect their above-mentioned differential effects on the employment of disabled and non-disabled people, combined with how much the local industry and occupational compositions deviate from their national averages. Components relating to unemployment, GVA per head and all supply-side and policy variables are much smaller, indicating that these factors are less important in explaining spatial variation in the DEG.

We can also use the decomposition results to compare the DEGs in two areas, as per equation (12). As an example, Figure 20 shows the decomposition of the DEG difference between Blackpool (in the North West of England) and Southampton (in the South East of England). These are two large urban areas at opposite ends of the country with very different DEGs and very different population and area level characteristics. The DEG in Blackpool is 39pp while the DEG in Southampton is 26pp. This raw difference of 13pp is shown by the lower bar in Figure 20. Our analysis finds that the difference in population characteristics accounts for about 5pp of this raw difference, as shown by the middle bar. In other words, we would expect the DEG in Blackpool still to be 8pp above that of Southampton even if both areas had the same population characteristics. This is akin to the area effect described above. The top bar in Figure 20 shows how this 8pp difference can be explained by area level characteristics. The difference between the DEGs would be still smaller if Blackpool were identical to Southampton with respect to unemployment, GVA per hour worked, industry profile, GPs per head and Social Fabric Index. However, if occupation profile, prevalence of Disability Confident employers and Universal Credit sanctions rate were the same in both places, then Blackpool would have an even higher DEG relative to Southampton. We can see that, among all area-level characteristics, industry composition dominates due to Southampton having more of its population working in knowledge services than Blackpool, relative to other services. If the industry composition in both areas were the same, the DEG difference would be reduced by over 3pp. The grey sector in the top bar shows that there remains a large residual (about 5.5pp), indicating that Blackpool would still have a much higher DEG than Southampton even if all individual and area level characteristics were equalised.

6.2.3 Summarising the full decomposition

The decompositions for all other ITL3 areas in Great Britain have also been calculated and the distribution of these data is summarised in Table 1. The full decomposition results are shown in Appendix 4. The standard deviation of the DEG difference across all areas is 5.3pp. The area at the tenth percentile has a DEG 8.4pp below the national average while the area at the ninetieth percentile has a DEG 6.0pp above the average. Table 1 shows that, on average, the second, third and fourth terms of the decomposition in equation (11) are of similar size, with a standard deviation of 2.2pp (absolute characteristics), 2.6pp (all area level characteristics) and 2.3pp (residual) respectively.[14]

As such, about a third of the spatial variation can be explained by population characteristics or 'people effects' which is a similar order of magnitude to the findings of Little (2009) where about a third of the spatial variation in inactivity rates due to sickness and disability can be attributed to compositional effects.

[14] We use the standard deviation as an intuitive measure of the spread of the DEGs and their components. The standard deviation of a component shows the amount of variation (in pp) that can be unambiguously assigned to that component alone, ignoring any co-variation with other components. The component standard deviations do not add up to the overall DEG standard deviation; nonetheless they still show the relative importance of the different components. To produce an exhaustive breakdown of the variation of DEG differences would require a variance decomposition involving many covariance terms that would arguably not be very informative and difficult to relate the observed percentage point differences in DEG.

The standard deviations reported in Table 1 also suggest that observed area level characteristics account for about half of the spatial variation in the DEG not explained by demographic characteristics. Industry composition is the most important area level characteristic, accounting for a component standard deviation of 2.5pp. This is dominated by the component for knowledge services, with a standard deviation of 2.7pp. Occupational composition is also important, accounting for a component standard deviation of 1.1pp. All other area components have a standard deviation of less than 1pp.

To some extent, this is consistent with the 'job queueing' theory outlined in section 2. Disabled people suffer more than non-disabled people from living in an area with weak labour demand, although it is the composition of this demand rather than the overall level that seems to matter most.

The bottom panel of Table 1 shows how the overall variation in the DEG would change if any one component were reduced to zero (keeping all other components unchanged). In other words, if all areas of Great Britain were exactly the same in a particular characteristic, how would the distribution of DEG differences change? If all areas had the same (absolute) demographic characteristics on average, the standard deviation of the DEG difference would reduce from 5.3pp to 3.8pp (a reduction of 28%) while if all areas had the same observed area level characteristics as nationally, the standard deviation would reduce to 4.1pp (-23%). On its own, eliminating all variation in industry composition would reduce the standard deviation to 4.7pp (-11%). This would mainly be achieved by making every area have the same proportion of people working in knowledge services, relative to other services. In contrast, eliminating all variation in occupational composition would increase the standard deviation to 5.8pp (+9%). While occupational composition is an important component, in many areas it predicts the DEG difference to be in the opposite direction than it actually is. For example, in Manchester (see Figure 19) the occupational composition of the city predicts the DEG to be lower than the national average when it is actually much higher. This effect is counteracted by the residual which is larger than it would be otherwise.

6.3 Supplementary analysis

An alternative approach to capturing spatial variation in the nature of labour demand is to use information on industry and occupational composition to construct indices of job quality. In the following analysis, we replace the industry and occupation variables with continuous scores to denote ability to work from home, access to flexible working arrangements and autonomy at work.

We add these variables to the vector $\mathbf{z}$ in equation (3), while removing the industry composition and occupational composition variables. The coefficients reveal that ability to work from home has a positive and significant effect on the employment of disabled people and a slight negative and marginally significant effect on the employment of non-disabled people. This is the expected direction for disabled people, indicating that they have a higher probability of being employed in areas with a high volume of jobs that can be done at home. The flexibility coefficient is negative in both equations, but nearly three times larger for disabled people. This means that living in an area with a high concentration of jobs offering flexible working reduces a disabled person's chances of being employed (conditional on all other individual and area level characteristics). The coefficients pertaining to autonomy at work are insignificant for both groups.

Table 2 shows a summary of the decomposition. In this alternative specification, area level characteristics together account for a standard deviation of 2.4pp (slightly lower than in the main decomposition). The largest component is ability to work from home with a standard deviation of 2.0pp. Eliminating all variation in the ability to work from home index would reduce the variation in the overall DEG from 5.3pp to 4.8pp. In contrast, eliminating all variation in the availability of flexible working would increase the DEG variation to 5.5pp.

We conduct a further supplementary analysis to include quality of public transport as an additional area level variable. Due to data availability, only ITL3 areas in England are included. Here quality of public transport is measured by the journey time to the nearest employment centre of 5,000 or more jobs as a proportion of the same journey time by car. The coefficient for public transport is insignificant for both disabled people and non-disabled people, when adding this variable to vector $\mathbf{z}$ in equation (3). A summary of the decomposition is shown in Table 3, revealing that the standard deviation of the public transport component is very small (0.1pp). We get the same result if we consider relative journey times to smaller employment centres (100-499 jobs) but the component is slightly larger when using absolute journey times by public transport (0.4pp for journey times to large employment centres and 0.2pp for journey times to smaller employment centres). These alternative measures are not shown in the tables.

7. Conclusion

The analysis presented in this paper provides clear evidence of spatial variation in the DEG that is not explained fully by 'people effects' (differences in the characteristics of the working age population). These remaining 'place effects', however, are not random but to some extent can be explained by variation in area level characteristics, particularly the nature of labour demand. It is clear that differences in underlying labour market conditions are not only driving overall employment rates but also the extent to which disabled people are accessing employment relative to their non-disabled counterparts. The types of jobs available in an area, indicated by industry and occupational composition, have a disproportionate effect on the employment of disabled people. It appears that a concentration of 'knowledge' industries (including information technology, finance, professional services and education) is particularly associated with a low DEG. In an alternative specification, having a high proportion of jobs that can be undertaken remotely is also found to be associated with a lower DEG. Keeping other area level factors constant, a high demand for lower skilled jobs (particularly elementary occupations such as cleaning and hospitality jobs) is also conducive to the employment rate of disabled people. However, spatial variations in healthcare capacity, social capital, transport, employer policies towards disability and benefit sanction rates explain a comparatively small component of the overall spatial variation in the DEG.

Given the importance of local factors, our results suggest that a one-size-fits-all approach to narrowing the DEG (for example by promoting skills) is at most a partial solution and may be less effective than locally adapted policies. Indeed the dual government priorities of levelling up the UK and narrowing the DEG may be highly symbiotic. Attracting high value private sector investment to left behind areas in Scotland, Wales and the north of England could help to boost the employment prospects of disabled people to a greater extent than their non-disabled counterparts, even if this employment is not concentrated in the most high skilled occupations. This may have a greater impact than more direct interventions such as investment in healthcare, public transport or community resources or an emphasis on policies towards the employment of disabled people. Levelling up, however, is not a magic bullet. In many areas, substantial residuals remain that cannot be explained by individual or area-level characteristics, indicating that spatial variation in the DEG would continue to exist even if all inequalities in economic outcomes were removed. This indicates that there is scope for bespoke regional interventions to address specific barriers to disabled people's labour market participation at a local level.

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Figures

Figure 1 – Difference from national DEG (2014-19) by ITL3 area

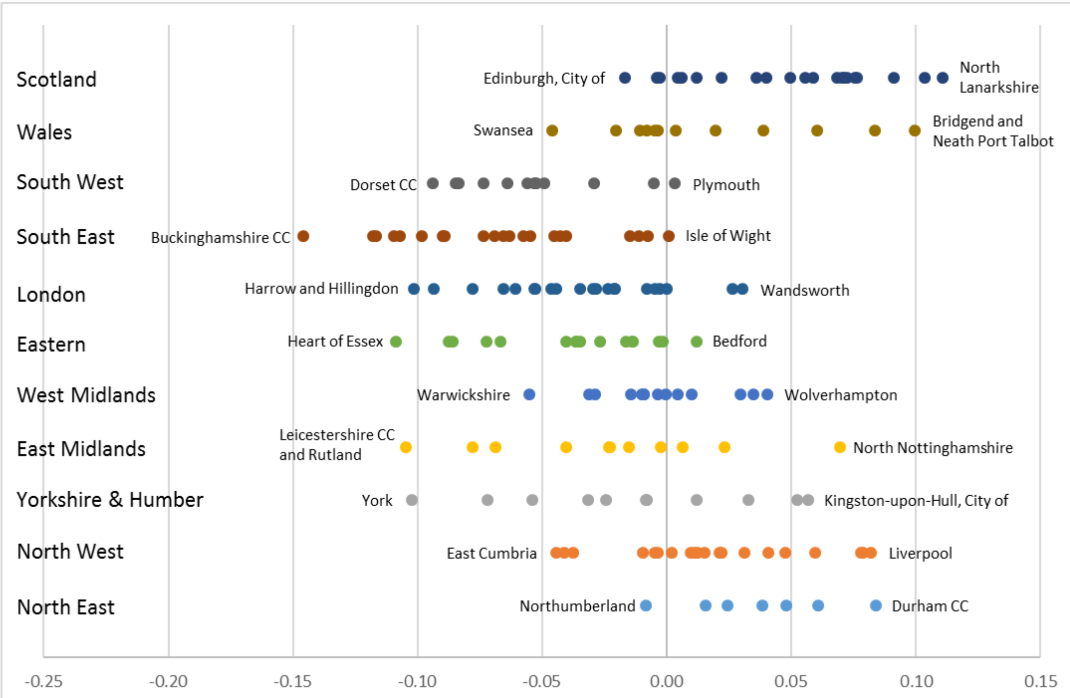


Figure 2 – Relationship between local unemployment rate and area fixed effects

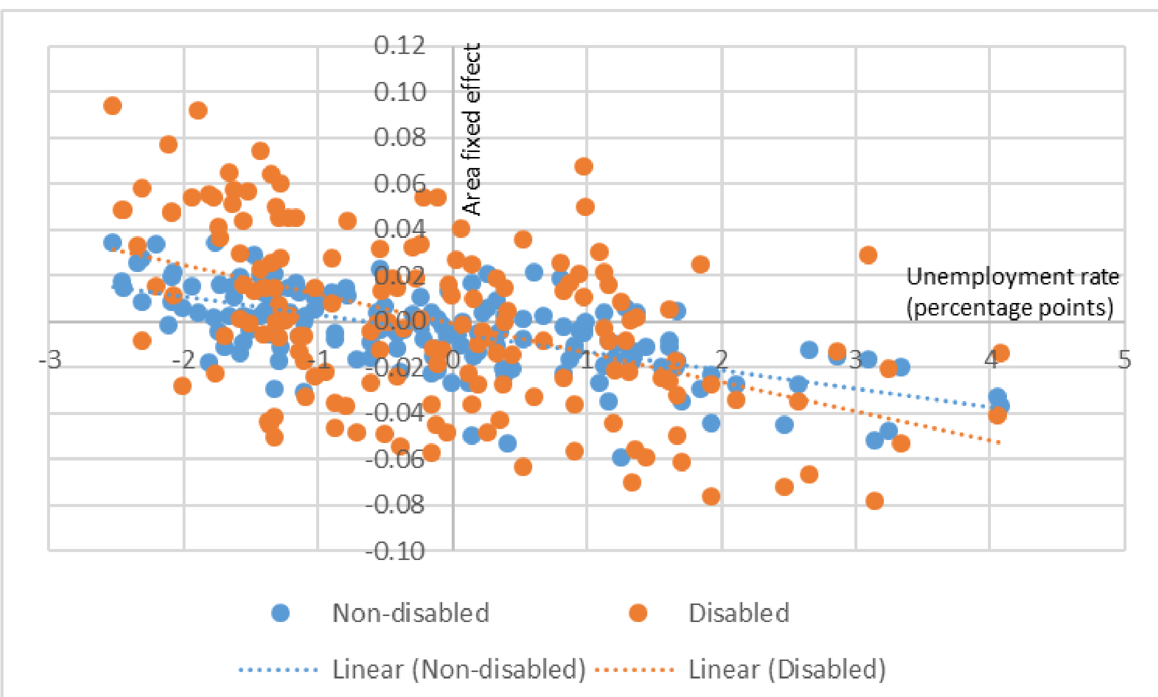


Figure 3 – Relationship between GVA and area fixed effects

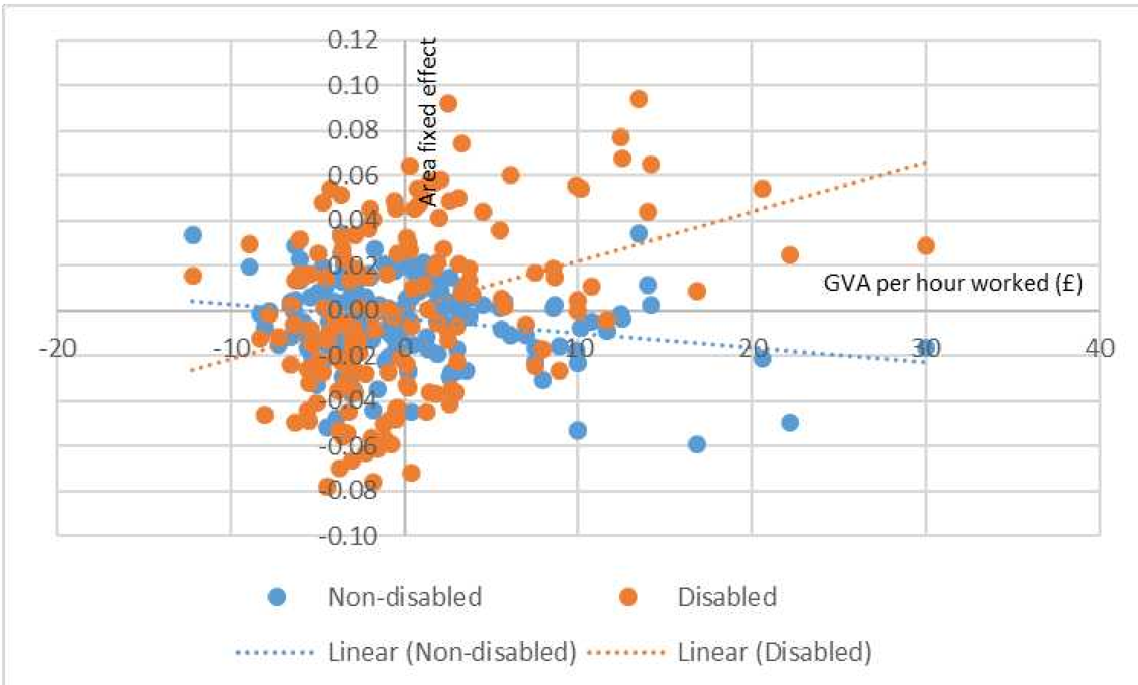


Figure 4 – Relationship between employment share in knowledge services and area fixed effects

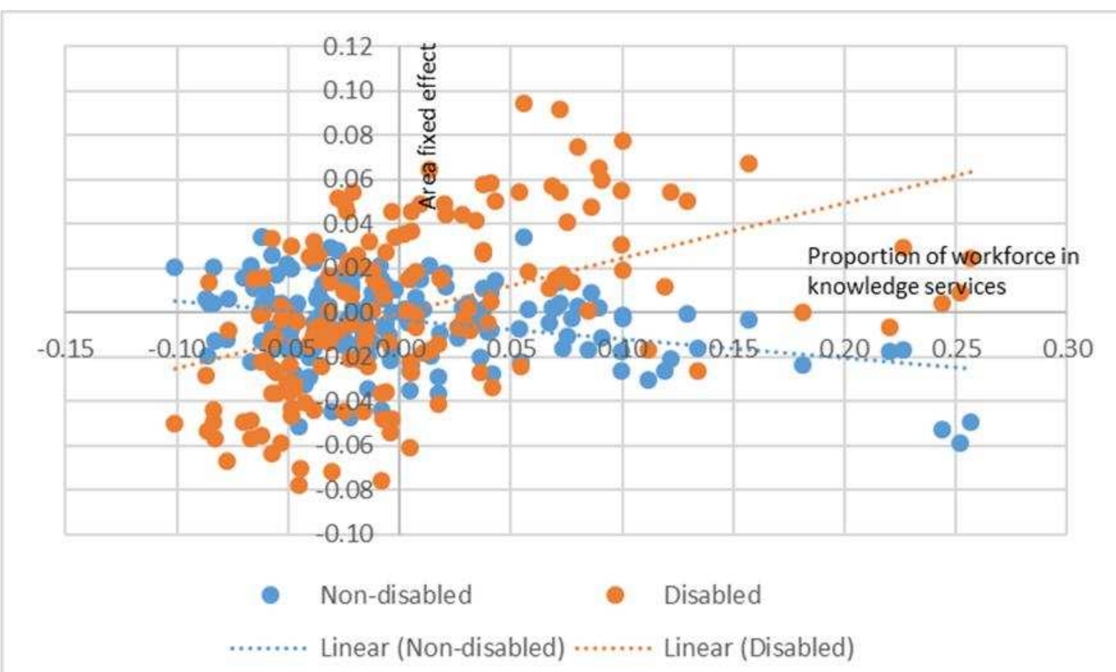


Figure 5 – Relationship between employment share in manufacturing and area fixed effects

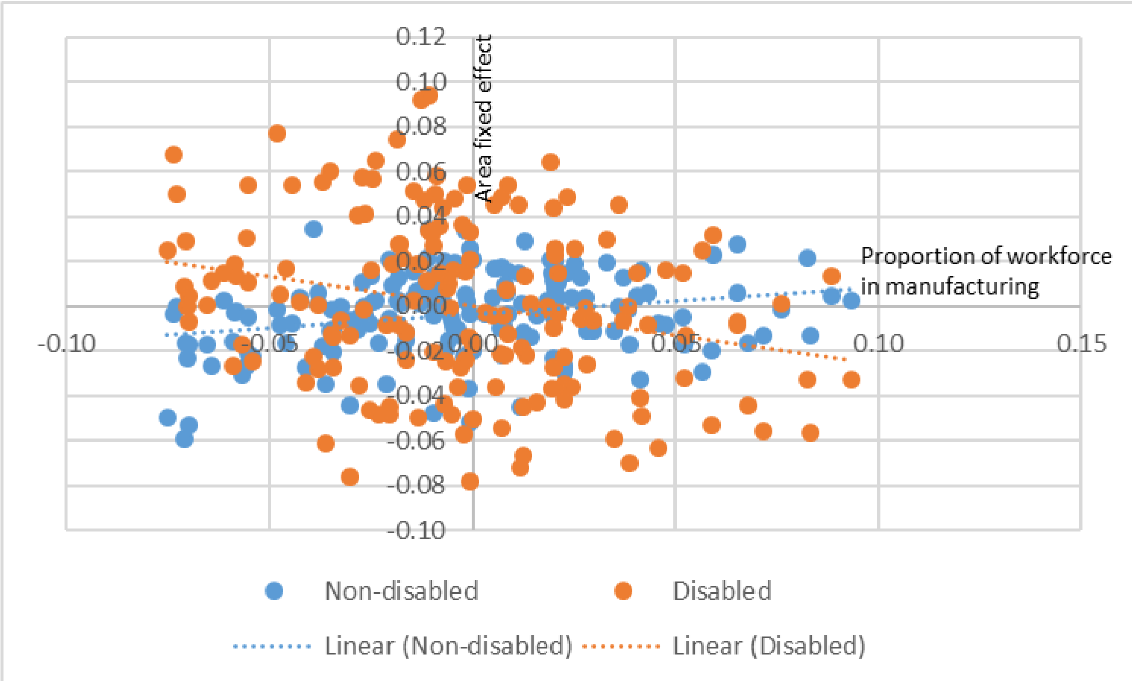


Figure 6 – Relationship between employment share in other production and area fixed effects

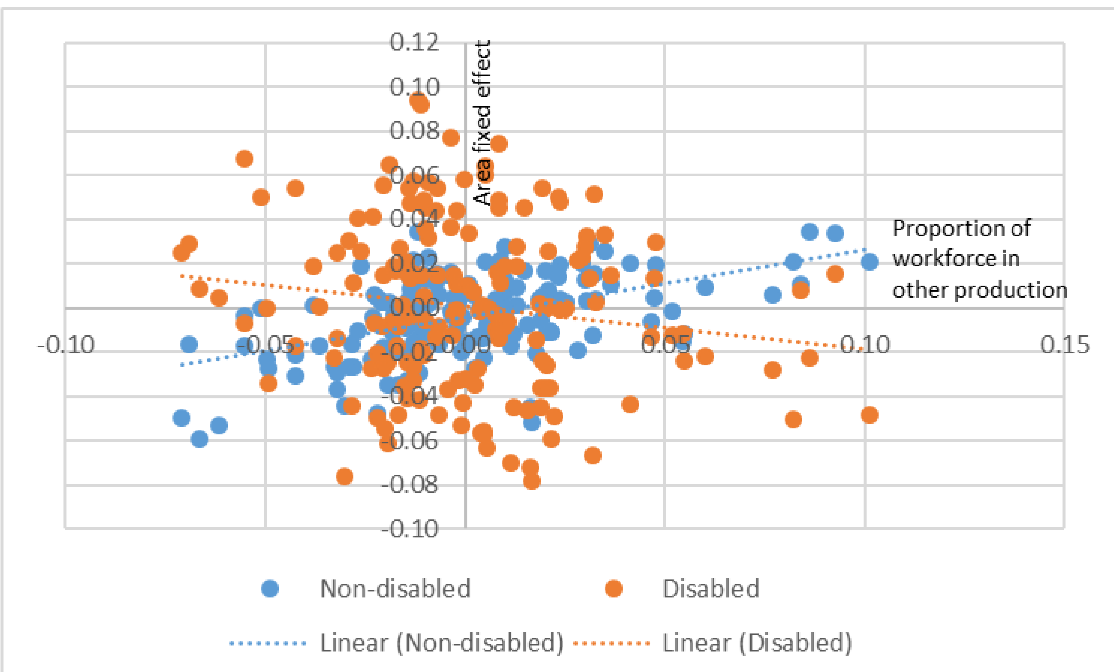


Figure 7 – Relationship between employment share in other services and area fixed effects

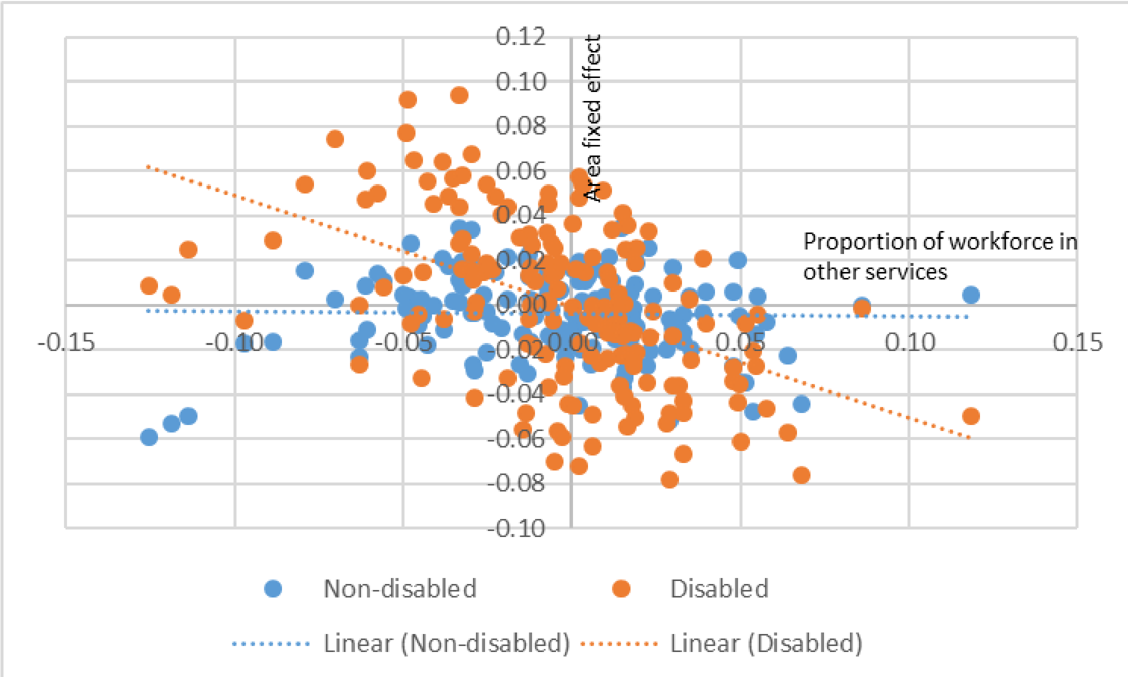


Figure 8 – Relationship between employment share in Level 4 occupations and area fixed effects

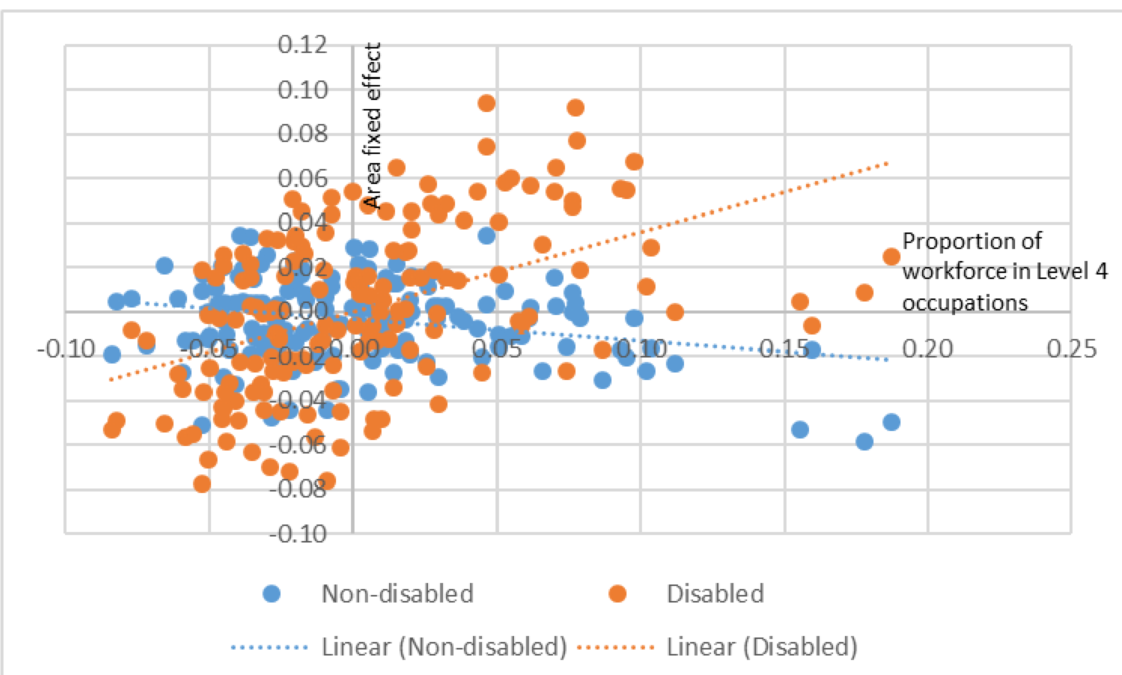


Figure 9 – Relationship between employment share in Level 3 occupations and area fixed effects

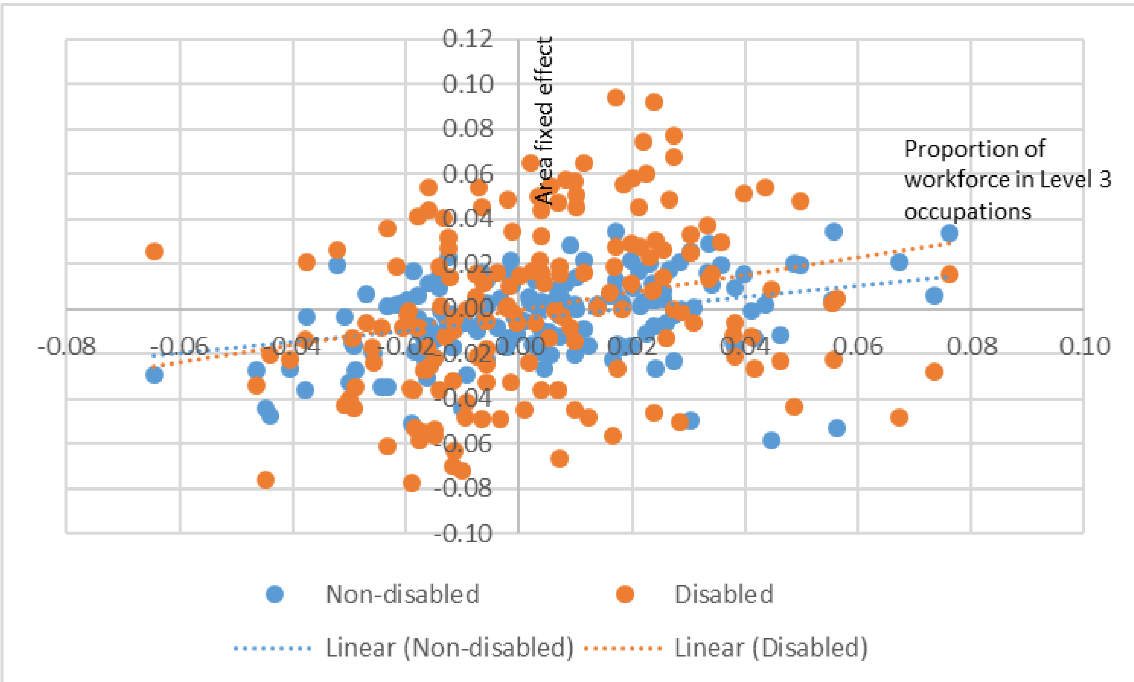


Figure 10 – Relationship between employment share in Level 2 occupations and area fixed effects

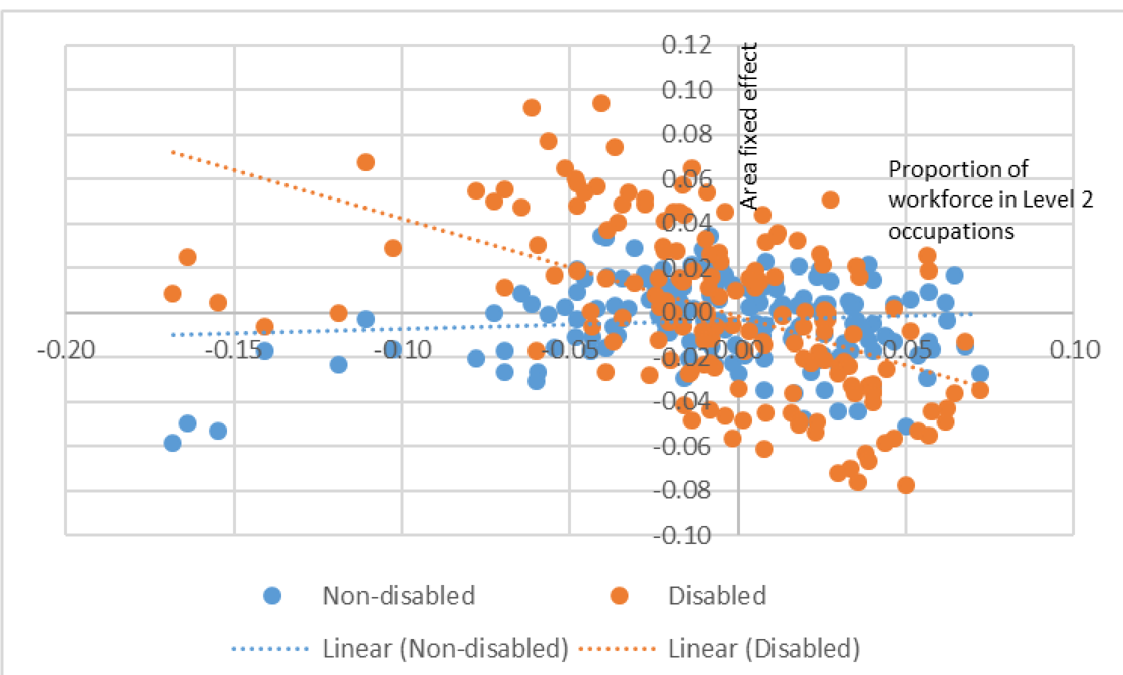


Figure 11 – Relationship between employment share in Level 1 occupations and area fixed effects

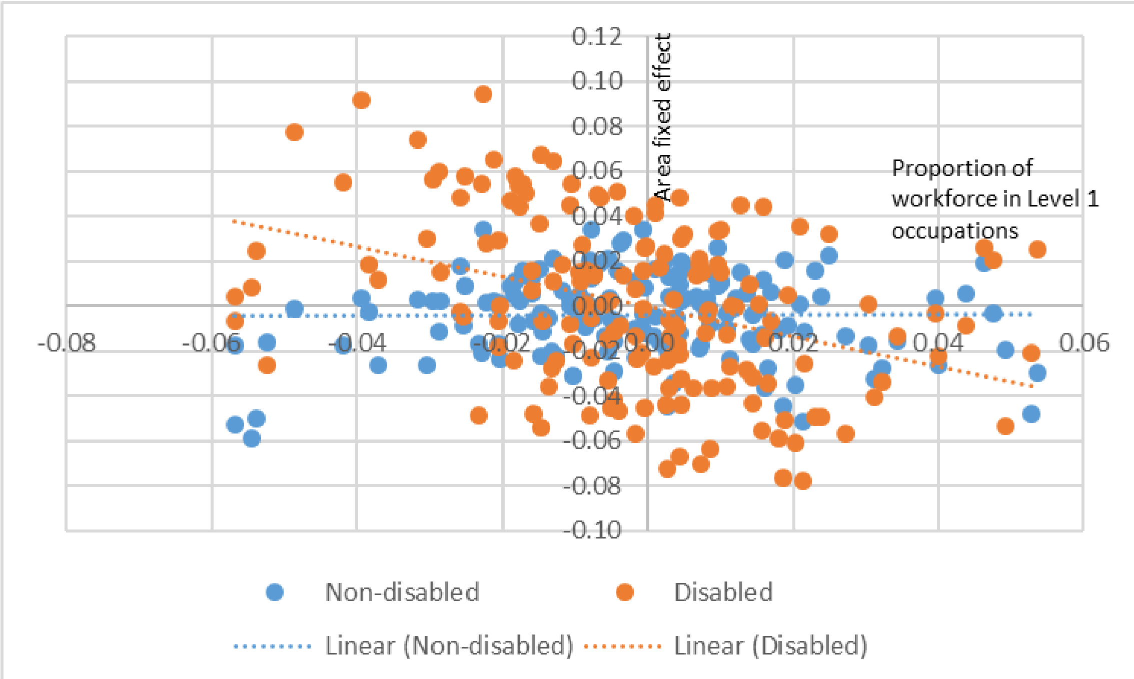


Figure 12 – Relationship between GPs per head and area fixed effects

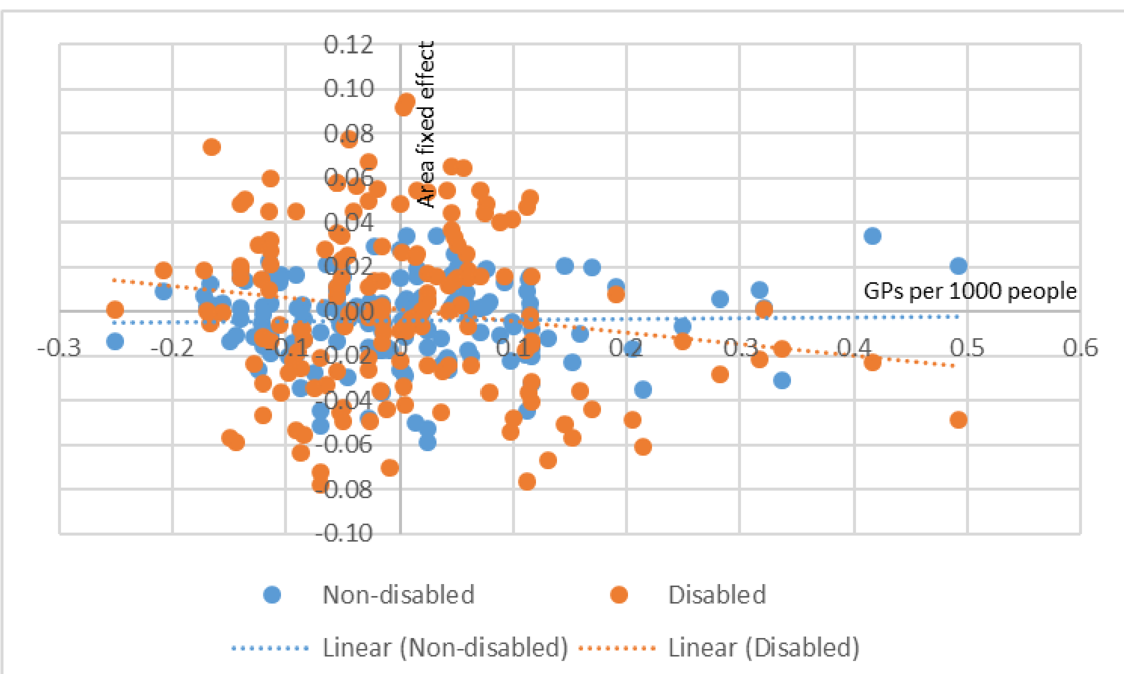


Figure 13 – Relationship between Social Fabric Index and area fixed effects

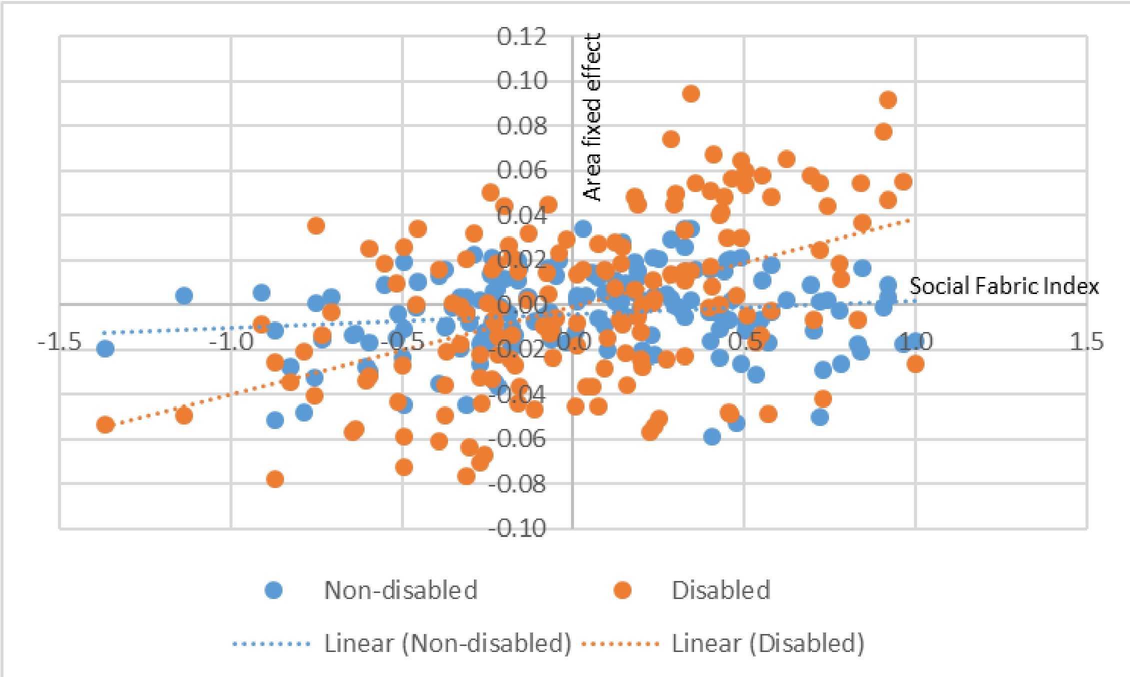


Figure 14 – Relationship between Disability Confident and area fixed effects

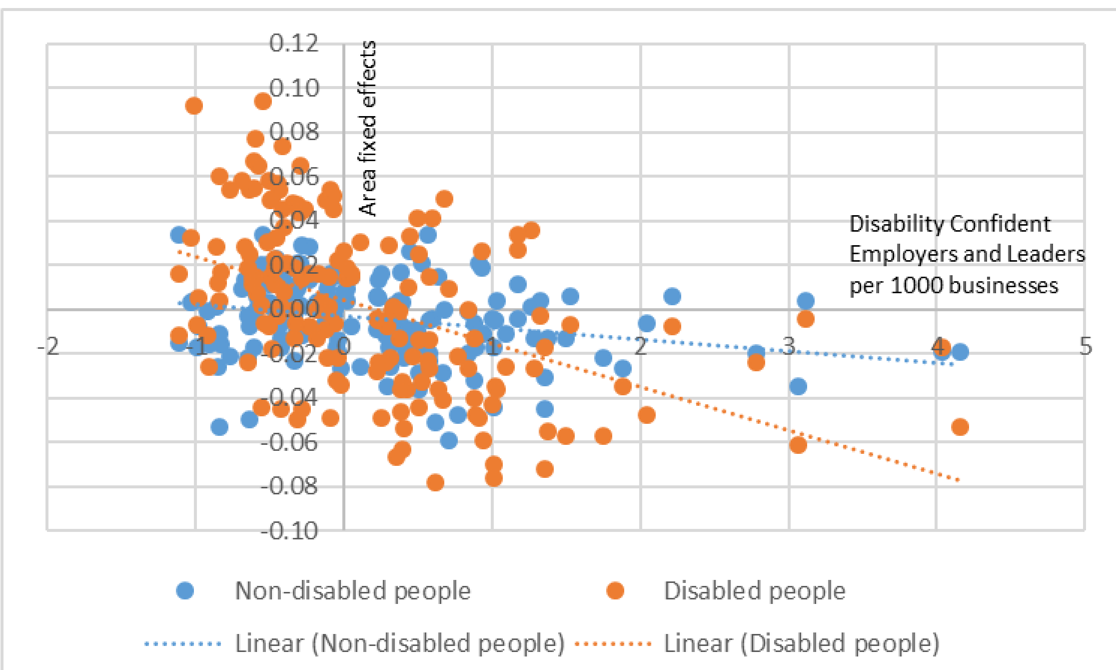


Figure 15 – Relationship between Universal Credit sanction rate and area fixed effects

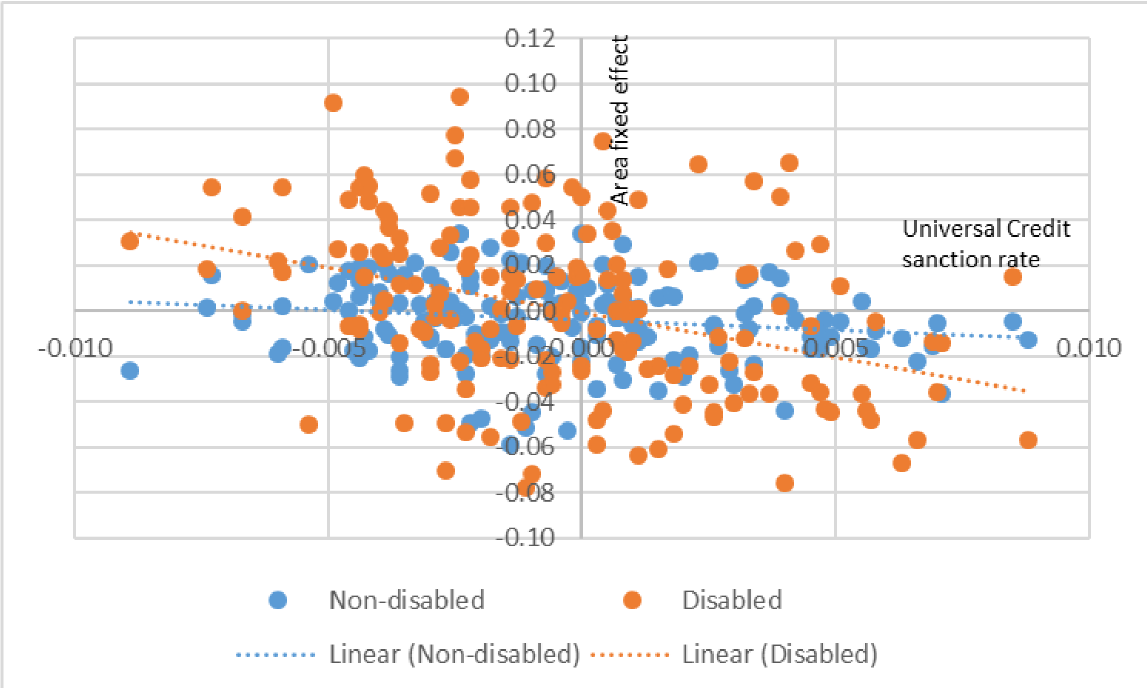


Figure 16 – Relationship between the actual DEG difference and the DEG difference explained by individual characteristics

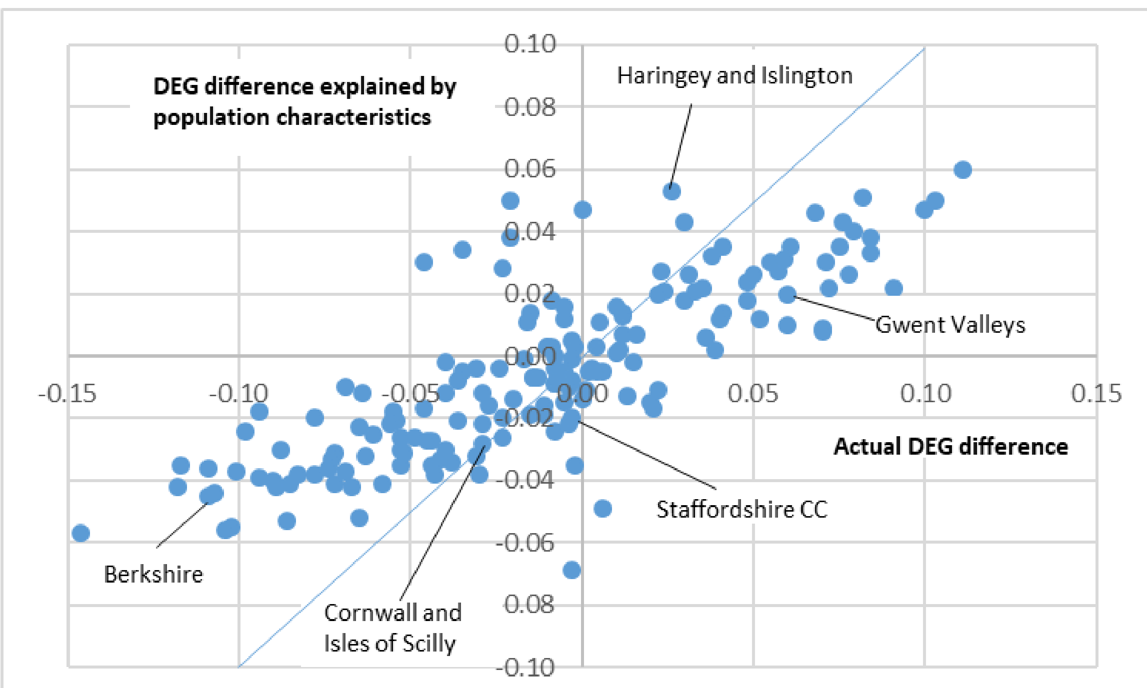


Figure 17 – DEG quintiles by ITL3 area[15]

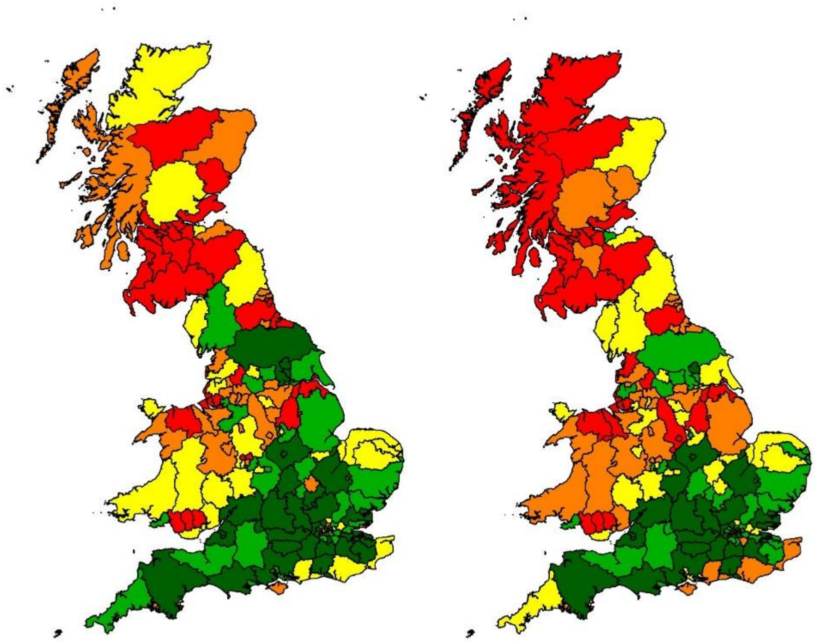
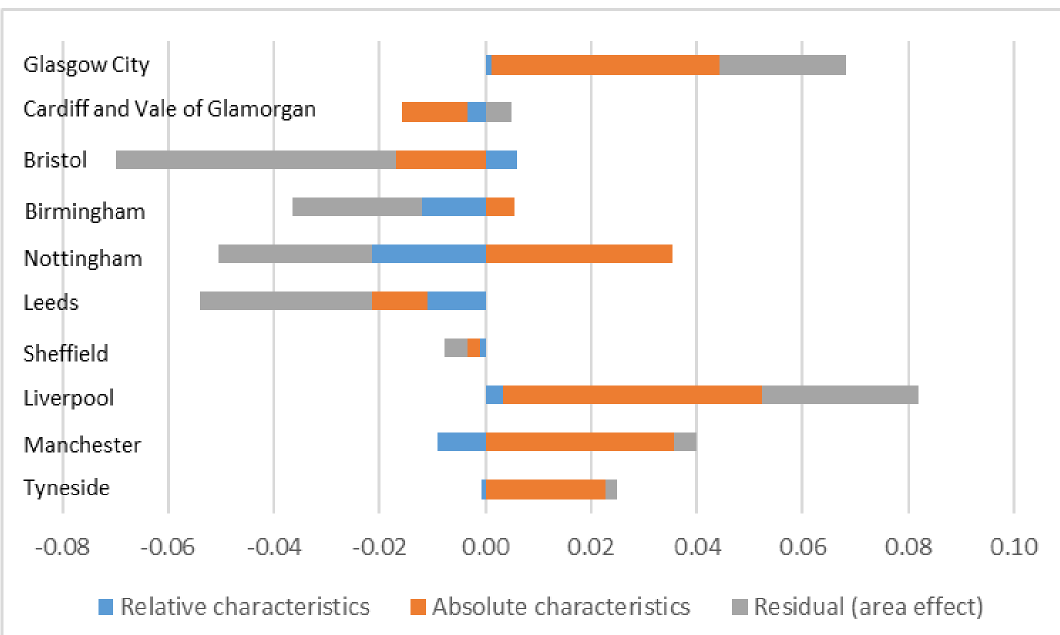


Figure 18 – Decomposition of the DEG difference for core cities



[15] Left map shows the raw DEG difference and right map shows the area effects. In both maps, red areas are in the highest quintile (largest / most positive DEG differences / area effects) and green areas are in the lowest quintile (smallest / most negative DEG differences / area effects).

Figure 19– Decomposition of the DEG difference for core cities, with area level factors

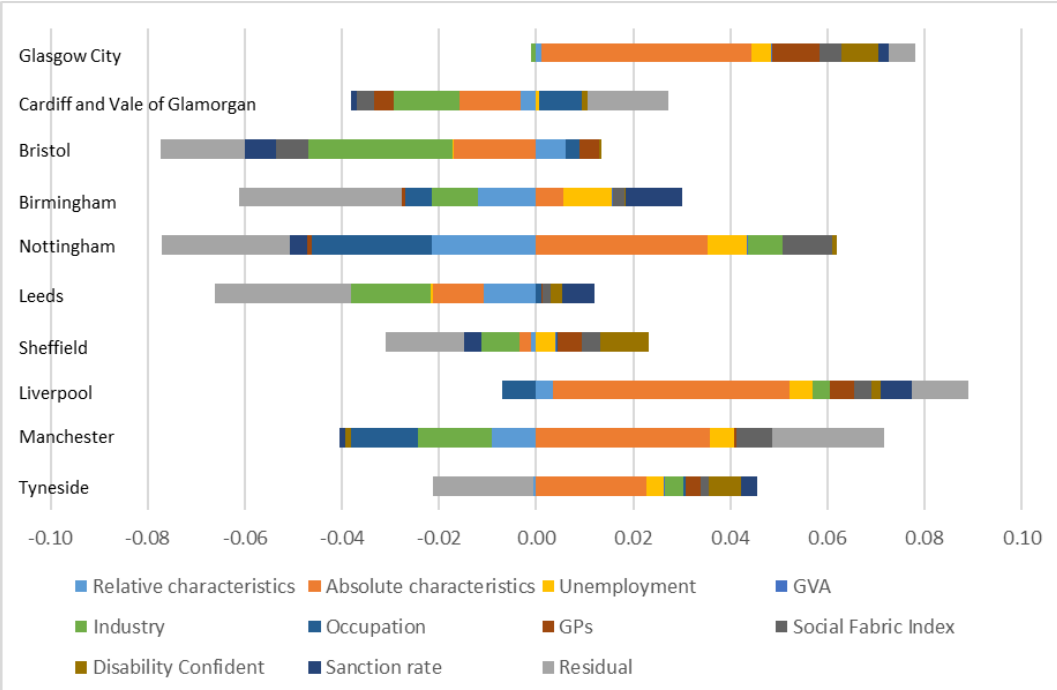


Figure 20– Decomposition of the DEG difference between Blackpool and Southampton

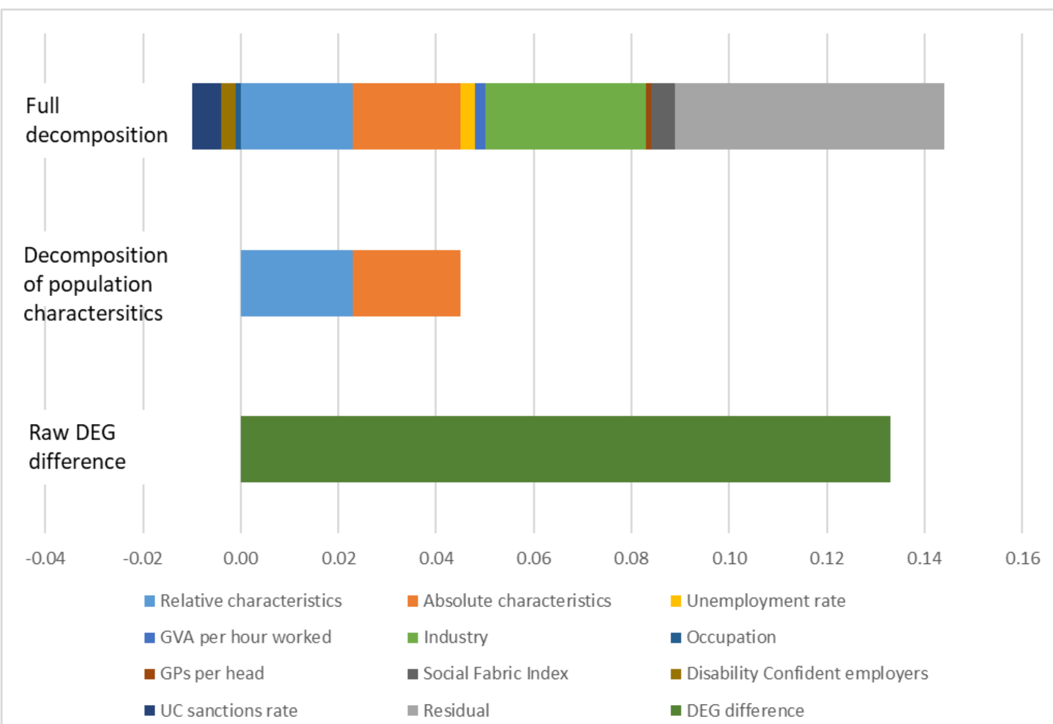


Table 1 – Summary of components across all areas

	Standard deviation	Minimum	10th percentile	90th percentile	Maximum
DEG difference	0.053	-0.146	-0.084	0.060	0.111
Components:					
Relative characteristics	0.011	-0.044	-0.015	0.013	0.038
Absolute characteristics	0.022	-0.053	-0.032	0.025	0.049
Unemployment rate	0.004	-0.007	-0.005	0.004	0.010
GVA per hour worked	0.001	-0.003	-0.001	0.000	0.001
Industries	0.025	-0.097	-0.035	0.021	0.037
Manufacturing	0.003	-0.008	-0.004	0.005	0.007
Other production	0.000	0.000	0.000	0.000	0.000
Knowledge services	0.027	-0.103	-0.038	0.022	0.037
Occupations	0.011	-0.025	-0.011	0.014	0.030
Level 4	0.026	-0.042	-0.022	0.042	0.103
Level 3	0.012	-0.031	-0.011	0.018	0.037
Level 2	0.023	-0.092	-0.031	0.019	0.036
GPs per head	0.005	-0.011	-0.005	0.005	0.022
Social Fabric Index	0.006	-0.015	-0.009	0.007	0.018
Disability Confident	0.003	-0.004	-0.003	0.002	0.010
Sanction rates	0.005	-0.013	-0.007	0.006	0.013
All area level characteristics	0.026	-0.087	-0.042	0.024	0.055
Residual + constant	0.023	-0.053	-0.031	0.029	0.065
DEG difference if component were reduced to zero:					
Relative characteristics	0.048	-0.143	-0.078	0.056	0.091
Absolute characteristics	0.038	-0.093	-0.057	0.042	0.077
Unemployment rate	0.051	-0.141	-0.080	0.060	0.111
GVA per hour worked	0.052	-0.146	-0.084	0.060	0.111
Industries	0.047	-0.116	-0.073	0.056	0.113
Manufacturing	0.054	-0.147	-0.085	0.066	0.111
Other production	0.053	-0.146	-0.084	0.060	0.111
Knowledge services	0.047	-0.115	-0.072	0.056	0.119
Occupations	0.058	-0.166	-0.096	0.067	0.112
Level 4	0.070	-0.190	-0.115	0.077	0.136
Level 3	0.056	-0.158	-0.093	0.065	0.119
Level 2	0.046	-0.111	-0.070	0.058	0.108
GPs per head	0.052	-0.146	-0.083	0.062	0.115
Social Fabric Index	0.050	-0.132	-0.077	0.062	0.109
Disability Confident	0.051	-0.142	-0.082	0.059	0.111
Sanction rates	0.051	-0.138	-0.078	0.063	0.105
All area level characteristics	0.041	-0.106	-0.062	0.048	0.108

Table 2 – Summary of components across all areas: Supplementary analysis with job type indices

	Standard deviation	Minimum	10th percentile	90th percentile	Maximum
DEG difference	0.053	-0.146	-0.084	0.060	0.111
Components:					
Relative characteristics	0.011	-0.044	-0.015	0.013	0.038
Absolute characteristics	0.022	-0.053	-0.032	0.025	0.049
Unemployment rate	0.002	-0.004	-0.003	0.002	0.006
GVA per hour worked	0.003	-0.014	-0.004	0.002	0.005
Homeworking index	0.020	-0.074	-0.026	0.018	0.027
Flexible working index	0.006	-0.014	-0.007	0.009	0.016
Autonomy at work index	0.003	-0.008	-0.004	0.003	0.005
GPs per head	0.006	-0.012	-0.006	0.006	0.024
Social Fabric Index	0.002	-0.004	-0.002	0.002	0.005
Disability Confident	0.003	-0.004	-0.003	0.002	0.010
Sanction rates	0.007	-0.018	-0.009	0.009	0.018
All area level characteristics	0.024	-0.087	-0.041	0.022	0.041
Residual + constant	0.024	-0.052	-0.033	0.032	0.062
DEG difference if component were reduced to zero:					
Relative characteristics	0.048	-0.143	-0.078	0.056	0.091
Absolute characteristics	0.038	-0.093	-0.057	0.042	0.077
Unemployment rate	0.052	-0.143	-0.082	0.060	0.111
GVA per hour worked	0.052	-0.145	-0.083	0.060	0.112
Homeworking index	0.048	-0.121	-0.076	0.062	0.105
Flexible working index	0.055	-0.149	-0.089	0.065	0.114
Autonomy at work index	0.051	-0.140	-0.082	0.059	0.108
GPs per head	0.052	-0.146	-0.083	0.062	0.116
Social Fabric Index	0.052	-0.142	-0.082	0.060	0.110
Disability Confident	0.051	-0.142	-0.082	0.059	0.111
Sanction rates	0.050	-0.136	-0.076	0.063	0.103
All area level characteristics	0.042	-0.096	-0.063	0.054	0.105

Table 3 – Summary of components across all areas: Supplementary analysis with public transport (England only)

	Standard deviation	Minimum	10th percentile	90th percentile	Maximum
DEG difference	0.048	-0.132	-0.075	0.051	0.098
Components:					
Relative characteristics	0.011	-0.025	-0.014	0.012	0.040
Absolute characteristics	0.022	-0.050	-0.030	0.027	0.052
Unemployment rate	0.003	-0.006	-0.004	0.003	0.008
GVA per hour worked	0.005	-0.025	-0.008	0.004	0.007
Industries	0.024	-0.085	-0.034	0.019	0.046
Manufacturing	0.004	-0.009	-0.005	0.006	0.008
Other production	0.007	-0.017	-0.010	0.008	0.021
Knowledge services	0.032	-0.114	-0.043	0.026	0.041
Occupations	0.018	-0.038	-0.017	0.023	0.052
Level 4	0.037	-0.061	-0.033	0.055	0.135
Level 3	0.012	-0.032	-0.012	0.018	0.032
Level 2	0.028	-0.104	-0.038	0.023	0.043
GPs per head	0.001	-0.001	-0.001	0.001	0.002
Social Fabric Index	0.010	-0.022	-0.016	0.011	0.028
Disability Confident	0.000	0.000	0.000	0.000	0.000
Sanction rates	0.005	-0.012	-0.006	0.006	0.013
Public transport	0.001	-0.004	-0.001	0.001	0.003
All area level characteristics	0.024	-0.075	-0.038	0.023	0.052
Residual + constant	0.021	-0.051	-0.026	0.022	0.065
DEG difference if component were reduced to zero:					
Relative characteristics	0.045	-0.131	-0.069	0.051	0.091
Absolute characteristics	0.034	-0.082	-0.054	0.035	0.088
Unemployment rate	0.046	-0.128	-0.071	0.047	0.095
GVA per hour worked	0.046	-0.130	-0.072	0.050	0.095
Industries	0.043	-0.105	-0.062	0.046	0.118
Manufacturing	0.049	-0.134	-0.077	0.054	0.102
Other production	0.048	-0.134	-0.074	0.052	0.103
Knowledge services	0.046	-0.101	-0.061	0.052	0.142
Occupations	0.058	-0.163	-0.093	0.064	0.115
Level 4	0.072	-0.187	-0.118	0.083	0.152
Level 3	0.053	-0.147	-0.083	0.065	0.118
Level 2	0.042	-0.097	-0.060	0.050	0.132
GPs per head	0.048	-0.132	-0.075	0.051	0.098
Social Fabric Index	0.042	-0.111	-0.062	0.043	0.093
Disability Confident	0.048	-0.132	-0.075	0.051	0.098
Sanction rates	0.047	-0.126	-0.073	0.050	0.101
Public transport	0.048	-0.132	-0.075	0.051	0.097
All area level characteristics	0.041	-0.106	-0.062	0.048	0.108

Appendix 1– Description of variables

Variable	Source	Description
Individual characteristics		
Sex	APS	Dummy variable: Female = 1.
Age group	APS	Four mutually exclusive dummy variables: Age 16-24; Age 25-34; Age 35-49; Age 50-64.
Marital status	APS	Dummy variable: Married = 1 if married, cohabiting or in a civil partnership.
Children	APS	Four dummy variables: Any dependent children aged under 2; aged 2-4; aged 5-9; or aged 10-15 respectively.
Sex and family interactions	APS	Five dummy variables: Female interacted with married; children aged under 2; children aged 2-4; children aged 5-9; and children aged 10-15 respectively.
Ethnicity	APS	Six mutually exclusive dummy variables: White; Mixed/multiple ethnic groups; Indian; Pakistani; Black/African/Caribbean/Black British; Other (Bangladeshi, Chinese, Any other Asian background and Other ethnic group).
Education	APS	Eleven mutually exclusive dummy variables denoting highest qualification attained: Degree; Level 4+ vocational; AS/A levels; Level 3 vocational; Apprenticeship; GCSEs grade A*-C; Level 2 vocational; GCSEs grade D-G; Level 1 vocational; Other; No qualifications.
Employment status of partner	APS Household dataset (Office for National Statistics, 2021a)	Two dummy variables: Whether partner is unemployed; Whether partner is economically inactive. Note that non-married people are coded 0 on both of these variables.
Housing tenure	APS	Five mutually exclusive dummy variables: Owned outright; being bought with mortgage or loan; part rent, part mortgage; rented; rent free.
Urban	APS	Dummy variable denoting whether the person lives in an urban area, derived from residency details.
Area characteristics		
Unemployment rate	NOMIS (Office for National Statistics, 2022b)	Average unemployment rate for people aged 16-64 over the six calendar years 2014 to 2019.
Gross Value Added (GVA) per hour worked	ONS Subregional Productivity release (Office for National Statistics, 2021b)	Nominal (smoothed) GVA per hour worked in pounds: average of the six years 2014 to 2019.
Share of employment by sector	2011 Census sourced from NOMIS (Office for National Statistics, 2011)	Proportion of the employed population working in Manufacturing (industry section C); Other production (industry sections A, B, D, E and F); Knowledge services (industry sections J, K, M and P); and Other services (industry sections G, H, I, L, N, O, Q, R, S and T) respectively. These groupings follow Department for Business, Innovation and Skills (2012).
Share of employment by occupation	2011 Census sourced from NOMIS (Office for National Statistics, 2011)	Proportion of the employed population working in Level 4 occupations (SOC codes starting in 11 and 2); Level 3 occupations (SOC codes starting in 12, 3 and 5); Level 2 occupations (SOC codes starting in 4, 6, 7 and 8); and Level 1 occupations (SOC codes starting in 9) respectively. This classification is provided by the Office for National Statistics.[16]

[16] www.ons.gov.uk/methodology/classificationsandstandards/standardoccupationalclassificationsoc/soc2020/soc2020volume1structureanddescriptionofunitgroups (Table 1) [Accessed 4 December 2023]

Homeworking index	2011 Census sourced from NOMIS (Office for National Statistics, 2011) combined with ONS data on 'ability to homework'[17]	Each four digit SOC code has an 'ability to homework' index where higher scores denote the occupation as being less suitable for homeworking. This information was used to calculate a weighted average homeworking score for each ITL3 area based on the concentration of occupations in that area.
Flexibility index	2011 Census sourced from NOMIS (Office for National Statistics, 2011) combined with UKHLS (University of Essex, 2021)	For each employed individual in Wave 10 of Understanding Society: The UK Household Longitudinal Study (UKHLS), we count how many flexible working arrangements are available to them (maximum of ten) and also observe the industry section and occupation in which they work. This information was used to calculate a weighted average flexibility score for each ITL3 area based on the concentration of industry and occupation combinations in that area.
Autonomy index	2011 Census sourced from NOMIS (Office for National Statistics, 2011) combined with UKHLS (University of Essex, 2021	For each employed individual in Wave 10 of UKHLS, we count how many areas of work in which they have at least some autonomy (maximum of five) and also observe the industry section and occupation in which they work. This information was used to calculate a weighted average autonomy score for each ITL3 area based on the concentration of industry and occupation combinations in that area.
GPs per 1,000 population	England: NHS Digital (2021); Wales: StatsWales (2020); Scotland: Public Health Scotland (2021). All combined with population estimates from Office for National Statistics (2022c)	Average number of GPs in post between 2015 and 2018 per thousand population. Note that some ITL3 areas in England and Wales have identical scores on this measure due to Clinical Commissioning Groups and Health Boards (the available spatial units for GP headcount data in England and Wales respectively) spanning more than one area.
Social Fabric Index	Onward (Tanner et al., 2020)	Index composed by Onward from a multitude of indicators across the four themes of economic value, relationships, positive norms and physical infrastructure.
Public transport	Department for Transport (2021) Journey Time Statistics (England only)	Average of the ratio of journey time by public transport and walking by the journey time by car to the nearest employment centre with more than 5,000 jobs available.[18]
Disability Confident employers per 1,000 businesses	List of Disability Confident employers (Department for Work and Pensions, 2018b) combined with UK Business Counts (Office for National Statistics, 2021c)	Number of employers that have progressed to the second (Employer) and third (Leader) levels of the Disability Confident scheme as a proportion of all businesses in the area.
Universal Credit sanctions rate	Department for Work and Pensions Stat-Xplore resource[19]	Number of sanctions applied as a proportion of the total caseload of Universal Credit claimants between April 2019 and March 2020.

17 www.ons.gov.uk/employmentandlabourmarket/peopleinwork/employmentandemployeetypes/articles/whichjobscanbedoneathome/2020-07-21 [Accessed 8 December 2023]

18 Three other public transport indicators were also generated from the same data: Average journey time by public transport and walking to the nearest employment centre with at least 5,000 jobs available; Average journey time by public transport and walking to the nearest employment centre with between 500 and 4,999 jobs available; Average of the ratio of journey time by public transport and walking by the journey time by car to the nearest employment centre with between 500 and 4,999 jobs available.

19 www.stat-xplore.dwp.gov.uk

Appendix 2– Coefficients from individual level equations (equation 2)

	Non-disabled people		Disabled people	
	$\widehat{\beta}^0$	Std. error	$\widehat{\beta}^1$	Std. error
Female	0.017***	(0.002)	0.082***	(0.004)
Age 25-34	0.292***	(0.002)	0.141***	(0.005)
Age 35-49	0.310***	(0.002)	0.096***	(0.004)
Age 50-64	0.209***	(0.002)	-0.002	(0.004)
Mixed ethnic groups	-0.045***	(0.005)	-0.035***	(0.012)
Indian	-0.063***	(0.003)	-0.039***	(0.009)
Pakistani	-0.146***	(0.004)	-0.117***	(0.008)
Black	-0.061***	(0.003)	-0.001	(0.009)
Other ethnic groups	-0.131***	(0.003)	-0.035***	(0.007)
Married	0.108***	(0.002)	0.292***	(0.004)
Female * Married	-0.096***	(0.002)	-0.178***	(0.005)
Children age 0-2	0.009***	(0.002)	0.046***	(0.008)
Female * Children age 0-2	-0.135***	(0.003)	-0.141***	(0.011)
Children age 2-4	0.001	(0.002)	0.055***	(0.007)
Female * Children age 2-4	-0.146***	(0.003)	-0.152***	(0.009)
Children age 5-9	0.009***	(0.001)	0.028***	(0.006)
Female * Children age 5-9	-0.085***	(0.002)	-0.073***	(0.007)
Children age 10-15	-0.025***	(0.002)	0.023***	(0.005)
Female * Children age 10-15	-0.034***	(0.002)	-0.048***	(0.006)
Level 4+ vocational	-0.017***	(0.002)	-0.050***	(0.005)
A-level	-0.072***	(0.002)	-0.109***	(0.005)
Level 3 vocational	0.015***	(0.002)	-0.042***	(0.005)
Apprenticeship	0.002	(0.002)	-0.127***	(0.006)
GCSEs A*-C	-0.085***	(0.001)	-0.164***	(0.004)
Level 2 vocational	-0.018***	(0.002)	-0.106***	(0.005)
GCSEs D-G	-0.072***	(0.003)	-0.201***	(0.007)
Level 1 vocational	-0.133***	(0.007)	-0.228***	(0.011)
Other qualification	-0.046***	(0.002)	-0.167***	(0.005)
No qualifications	-0.189***	(0.002)	-0.331***	(0.004)
Urban	0.004***	(0.001)	-0.007**	(0.004)
Mortgage	0.114***	(0.001)	0.141***	(0.003)
Part rent	0.109***	(0.006)	0.088***	(0.017)
Rented	0.033***	(0.002)	-0.081***	(0.003)
Rent free	0.037***	(0.006)	-0.028**	(0.013)
Partner unemployed	-0.069***	(0.004)	-0.122***	(0.009)
Partner inactive	-0.163***	(0.002)	-0.243***	(0.004)
N	791,401		195,455	

****p<0.01 **p<0.05 *p<0.1; Omitted categories: Age 16-24, White, Degree, Owned outright*

Appendix 3 – Coefficients from area level equations (equation 3)

	Non-disabled people $\hat{\gamma}^0$	Disabled people $\hat{\gamma}^1$
Unemployment rate	-0.009***	-0.012***
	(0.001)	(0.002)
GVA per hour worked	0.000	0.000
	(0.000)	(0.001)
Proportion of employed population in manufacturing	0.087**	0.175*
	(0.039)	(0.089)
Proportion of employed population in other production	0.055	0.054
	(0.067)	(0.153)
Proportion of employed population in knowledge services	0.160***	0.553***
	(0.058)	(0.131)
Proportion of employed population in Level 4 occupations	-0.393***	-0.929***
	(0.109)	(0.247)
Proportion of employed population in Level 3 occupations	-0.029	-0.507**
	(0.091)	(0.207)
Proportion of employed population in Level 2 occupations	-0.062	-0.594***
	(0.090)	(0.203)
GPs per 100 population	0.004	-0.041*
	(0.009)	(0.021)
Social Fabric Index	0.001	0.014
	(0.005)	(0.011)
Disability Confident Employers and Leaders per 1000 businesses	0.001	-0.004
	(0.001)	(0.003)
Universal Credit sanctions rate	-0.435	-2.089***
	(0.279)	(0.632)
Constant	0.673***	0.953***
	(0.067)	(0.150)
N	166	166

****p<0.01 **p<0.05 *p<0.1; Omitted categories: Proportion of employed population in other services; Proportion of employed population in Level 1 occupations.*

Appendix 4 – Full decomposition results (main specification)

	DEG diff	Relative characteristics	Absolute characteristics	Unemp rate	GVA per hour worked	Manuf-acturing	Other product-ion	Know-ledge services	Level 4	Level 3	Level 2	GPs per 1000 pop	Social Fabric Index	DC per 1000 firms	UC sanction rate	Residual + Constant
UKC11 Hartlepool and Stockton-on-Tees	0.061	0.007	0.028	0.006	0.000	-0.001	0.000	0.009	-0.009	-0.004	0.014	-0.003	0.006	0.003	-0.002	0.007
UKC12 South Teesside	0.048	0.002	0.022	0.008	0.000	0.000	0.000	0.015	-0.025	-0.009	0.024	-0.003	0.011	0.001	-0.002	0.004
UKC13 Darlington	0.016	-0.004	0.011	0.003	0.000	0.000	0.000	0.004	-0.006	-0.003	0.011	-0.003	0.004	0.000	-0.003	0.002
UKC14 Durham CC	0.084	0.025	0.007	0.003	0.000	-0.003	0.000	0.015	-0.013	-0.005	0.015	0.000	0.003	0.002	-0.005	0.039
UKC21 Northumberland	-0.008	-0.005	0.005	0.001	0.000	0.000	0.000	0.014	-0.004	0.005	0.002	0.005	-0.002	0.001	-0.006	-0.024
UKC22 Tyneside	0.024	0.00	0.02	0.004	0.000	0.001	0.000	0.003	-0.001	-0.012	0.014	0.003	0.002	0.007	0.003	-0.021
UKC23 Sunderland	0.038	-0.001	0.034	0.006	0.000	-0.002	0.000	0.016	-0.029	-0.013	0.036	-0.003	0.011	0.004	-0.004	-0.016
UKD11 West Cumbria	-0.010	-0.007	0.008	-0.002	0.000	-0.008	0.000	0.031	-0.018	0.012	0.001	0.002	-0.001	-0.001	0.001	-0.030
UKD12 East Cumbria	-0.044	-0.020	-0.015	-0.006	0.000	0.000	0.000	0.020	-0.013	0.015	-0.008	0.002	-0.005	0.000	-0.004	-0.010
UKD33 Manchester	0.031	-0.01	0.04	0.005	0.000	0.004	0.000	-0.019	0.010	-0.022	-0.002	0.000	0.008	-0.001	-0.001	0.023
UKD34 Greater Manchester South West	0.010	0.000	0.001	0.001	0.000	0.002	0.000	-0.015	0.018	-0.010	-0.001	-0.004	-0.001	-0.002	-0.005	0.026
UKD35 Greater Manchester South East	0.015	0.000	-0.002	-0.001	0.000	-0.001	0.000	-0.006	0.004	-0.002	0.010	-0.004	-0.001	-0.002	0.001	0.019
UKD36 Greater Manchester North West	0.022	0.010	0.009	0.000	0.000	-0.002	0.000	0.012	-0.012	-0.005	0.016	0.000	0.000	-0.001	-0.005	-0.001
UKD37 Greater Manchester North East	0.002	-0.010	0.006	0.003	0.000	-0.001	0.000	0.005	-0.008	-0.007	0.015	-0.004	0.002	-0.001	-0.002	0.005
UKD41 Blackburn with Darwen	0.013	-0.023	0.009	0.003	0.000	-0.006	0.000	0.013	-0.014	-0.013	0.028	0.000	0.003	0.000	0.009	0.003
UKD42 Blackpool	0.078	0.008	0.019	0.004	0.001	0.001	0.000	0.030	-0.041	-0.001	0.031	-0.001	0.015	-0.001	-0.005	0.019
UKD44 Lancaster and Wyre	0.021	-0.006	-0.009	-0.004	0.000	0.002	0.000	0.004	0.001	0.001	0.002	-0.002	-0.002	-0.002	0.004	0.034
UKD45 Mid Lancashire	-0.004	0.002	-0.022	-0.004	0.000	-0.002	0.000	0.006	0.011	-0.002	-0.003	-0.007	-0.003	0.000	-0.001	0.023
UKD46 East Lancashire	0.060	0.004	0.004	0.001	0.000	-0.007	0.000	0.017	-0.014	-0.001	0.018	-0.003	0.002	0.000	0.004	0.033
UKD47 Chorley and West Lancashire	-0.005	0.010	0.002	-0.004	0.000	-0.001	0.000	0.002	0.012	-0.001	-0.008	-0.011	-0.004	-0.002	0.002	-0.002
UKD61 Warrington	-0.038	-0.012	-0.021	-0.004	0.000	0.001	0.000	-0.005	0.018	-0.009	-0.007	-0.002	-0.006	0.000	0.001	0.009
UKD62 Cheshire East	-0.041	-0.006	-0.028	-0.005	-0.001	-0.002	0.000	-0.013	0.034	0.000	-0.026	0.000	-0.010	-0.002	0.007	0.010
UKD63 Cheshire West and Chester	0.011	0.011	-0.011	-0.004	0.000	-0.002	0.000	-0.010	0.019	-0.004	-0.011	0.000	-0.011	0.001	0.003	0.028
UKD71 East Merseyside	0.079	0.008	0.034	0.001	0.000	-0.001	0.000	0.016	-0.022	-0.014	0.031	-0.002	0.006	0.002	0.008	0.014
UKD72 Liverpool	0.082	0.00	0.05	0.005	0.000	0.003	0.000	0.001	-0.002	-0.021	0.016	0.005	0.004	0.002	0.006	0.012

UKD73 Sefton	0.041	0.007	0.006	-0.003	0.000	0.003	0.000	0.000	-0.001	-0.009	0.019	-0.001	-0.003	0.002	0.011	0.009
UKD74 Wirral	0.048	0.007	0.011	-0.001	0.000	0.000	0.000	-0.001	0.006	-0.007	0.010	0.004	-0.004	0.000	0.003	0.020
UKE11 Kingston upon Hull, City of	0.057	-0.003	0.028	0.008	0.000	-0.005	0.000	0.031	-0.042	-0.009	0.026	-0.004	0.018	0.010	-0.004	0.001
UKE12 East Riding of Yorkshire	-0.031	-0.008	-0.024	-0.004	0.000	-0.001	0.000	0.010	0.008	0.009	-0.012	-0.007	-0.004	-0.002	-0.001	0.005
UKE13 North and North East Lincolnshire	0.052	0.002	0.008	0.002	0.000	-0.007	0.000	0.030	-0.029	-0.007	0.022	-0.007	0.008	0.003	0.014	0.011
UKE21 York	-0.102	-0.026	-0.028	-0.005	0.000	0.002	0.000	-0.016	0.023	-0.008	-0.014	0.005	-0.007	0.001	-0.011	-0.017
UKE22 North Yorkshire CC	-0.072	-0.013	-0.029	-0.006	0.000	0.001	0.000	0.007	0.005	0.024	-0.028	0.004	-0.003	-0.002	-0.007	-0.026
UKE31 Barnsley, Doncaster and Rotherham	0.033	0.006	0.014	0.004	0.000	-0.002	0.000	0.020	-0.024	-0.007	0.021	-0.004	0.011	0.002	0.002	-0.011
UKE32 Sheffield	-0.008	0.00	0.00	0.004	0.000	0.000	0.000	-0.008	0.013	-0.012	-0.001	0.005	0.004	0.010	-0.003	-0.016
UKE41 Bradford	-0.008	-0.015	0.006	0.005	0.000	-0.002	0.000	-0.005	-0.010	-0.008	0.014	0.002	0.006	0.001	0.005	-0.007
UKE42 Leeds	-0.054	-0.01	-0.01	0.000	0.000	0.001	0.000	-0.017	0.012	-0.006	-0.006	0.000	0.002	0.002	0.007	-0.028
UKE44 Calderdale and Kirklees	-0.024	0.002	-0.004	-0.001	0.001	-0.004	0.000	-0.004	0.004	0.000	0.000	-0.005	0.000	0.001	0.014	-0.026
UKE45 Wakefield	0.012	-0.002	0.009	0.003	0.000	-0.002	0.000	0.018	-0.022	-0.009	0.012	0.001	0.009	0.003	-0.001	-0.007
UKF11 Derby	0.006	-0.008	0.004	0.000	0.000	-0.006	0.000	0.012	-0.002	-0.012	0.008	0.001	0.002	0.003	-0.002	0.007
UKF12 East Derbyshire	0.023	0.016	0.011	-0.002	0.000	-0.003	0.000	0.017	-0.013	-0.004	0.012	0.001	0.006	0.001	-0.011	-0.008
UKF13 South and West Derbyshire	-0.002	-0.012	-0.024	-0.006	0.000	-0.006	0.000	0.008	0.005	0.005	-0.008	0.000	-0.003	-0.002	-0.003	0.043
UKF14 Nottingham	-0.015	-0.02	0.04	0.008	0.000	0.001	0.000	0.006	-0.012	-0.021	0.008	-0.001	0.010	0.001	-0.003	-0.026
UKF15 North Nottinghamshire	0.070	0.000	0.007	-0.002	0.000	-0.004	0.000	0.025	-0.019	-0.003	0.010	-0.002	0.004	0.000	-0.006	0.058
UKF16 South Nottinghamshire	-0.023	-0.001	-0.019	-0.001	0.000	0.000	0.000	-0.014	0.035	0.000	-0.021	-0.001	-0.009	-0.002	-0.005	0.015
UKF21 Leicester	-0.078	-0.023	0.001	0.004	0.000	-0.005	0.000	0.014	-0.021	-0.031	0.027	-0.002	0.007	0.000	-0.006	-0.045
UKF22 Leicestershire CC and Rutland	-0.104	-0.021	-0.037	-0.004	0.000	-0.003	0.000	-0.001	0.013	0.005	-0.012	-0.002	-0.005	-0.002	-0.004	-0.033
UKF24 West Northamptonshire	-0.069	-0.010	-0.026	-0.004	0.000	-0.001	0.000	-0.005	0.009	-0.002	-0.012	-0.005	-0.003	-0.001	-0.004	-0.004
UKF25 North Northamptonshire	-0.040	-0.009	-0.020	-0.002	0.001	-0.005	0.000	0.013	-0.009	-0.005	0.002	-0.005	0.003	-0.002	-0.002	0.001
UKF30 Lincolnshire	-0.023	-0.016	-0.009	-0.002	0.000	-0.002	0.000	0.022	-0.014	0.003	0.005	-0.007	0.004	0.000	-0.007	0.001
UKG11 Herefordshire, County of	-0.010	0.002	0.000	-0.004	0.001	-0.003	0.000	0.016	-0.007	0.018	-0.014	0.002	-0.007	-0.003	-0.001	-0.011
UKG12 Worcestershire	-0.009	0.013	-0.010	-0.004	0.000	-0.003	0.000	0.002	0.013	0.004	-0.012	0.002	-0.002	-0.001	0.000	-0.011
UKG13 Warwickshire	-0.055	0.002	-0.021	-0.007	0.000	-0.002	0.000	-0.006	0.020	-0.001	-0.020	0.000	-0.007	-0.001	0.002	-0.013

UKG21 Telford and Wrekin	0.005	0.001	0.008	-0.001	0.000	-0.007	0.000	0.010	-0.012	-0.006	0.011	-0.001	0.004	-0.001	-0.003	0.000
UKG22 Shropshire CC	0.000	-0.005	-0.009	-0.004	0.001	-0.001	0.000	0.010	0.003	0.017	-0.019	-0.001	-0.005	-0.002	0.001	0.014
UKG23 Stoke-on-Trent	0.030	0.000	0.018	0.003	0.000	-0.004	0.000	0.028	-0.039	-0.008	0.025	0.000	0.012	0.005	-0.007	-0.003
UKG24 Staffordshire CC	-0.003	-0.008	-0.013	-0.003	0.000	-0.003	0.000	0.011	0.003	0.002	-0.006	-0.005	0.000	-0.003	-0.007	0.028
UKG31 Birmingham	-0.031	-0.01	0.01	0.010	0.000	0.000	0.000	-0.010	0.005	-0.018	0.007	-0.001	0.002	0.000	0.012	-0.034
UKG32 Solihull	-0.014	-0.001	-0.007	-0.002	-0.001	0.000	0.000	-0.018	0.033	-0.005	-0.014	-0.001	-0.008	0.000	0.009	0.000
UKG33 Coventry	-0.029	-0.020	-0.002	0.000	0.000	-0.002	0.000	-0.005	-0.009	-0.019	0.009	0.000	0.003	0.000	0.005	0.011
UKG36 Dudley	-0.009	0.000	0.017	0.003	0.000	-0.004	0.000	0.010	-0.010	-0.001	0.017	0.005	0.002	-0.001	0.005	-0.053
UKG37 Sandwell	0.010	-0.017	0.031	0.007	0.000	-0.004	0.000	0.020	-0.036	-0.014	0.033	0.005	0.009	0.000	0.011	-0.037
UKG38 Walsall	0.035	0.005	0.017	0.004	0.000	-0.004	0.000	0.017	-0.020	-0.005	0.019	0.005	0.007	-0.001	0.007	-0.016
UKG39 Wolverhampton	0.041	-0.001	0.035	0.010	0.000	-0.003	0.000	0.014	-0.019	-0.014	0.019	0.005	0.010	0.001	0.005	-0.022
UKH11 Peterborough	-0.003	0.008	-0.002	0.002	0.000	-0.002	0.000	0.005	-0.018	-0.015	0.010	0.001	0.006	0.002	-0.007	0.008
UKH12 Cambridgeshire CC	-0.072	-0.002	-0.029	-0.005	0.000	-0.001	0.000	-0.031	0.040	-0.003	-0.027	0.001	-0.006	-0.001	-0.012	0.004
UKH14 Suffolk	-0.035	0.001	-0.005	-0.003	0.000	0.000	0.000	0.007	-0.007	0.010	-0.004	-0.004	0.000	-0.002	-0.002	-0.025
UKH15 Norwich and East Norfolk	-0.016	-0.007	0.016	-0.001	0.000	0.001	0.000	-0.002	-0.008	0.000	0.003	-0.002	0.005	0.002	0.000	-0.025
UKH16 North and West Norfolk	-0.014	-0.004	-0.003	-0.003	0.000	-0.002	0.000	0.023	-0.023	0.017	-0.001	-0.002	0.001	-0.003	-0.007	-0.007
UKH17 Breckland and South Norfolk	-0.013	0.004	-0.013	-0.004	0.000	-0.002	0.000	0.006	-0.008	0.011	-0.005	-0.002	0.000	-0.002	-0.007	0.007
UKH21 Luton	-0.067	-0.013	-0.028	0.002	0.000	0.000	0.000	0.007	-0.021	-0.018	0.016	-0.006	0.004	-0.002	0.001	-0.008
UKH23 Hertfordshire	-0.088	-0.002	-0.029	-0.004	0.000	0.002	0.000	-0.030	0.036	0.005	-0.025	-0.002	-0.007	-0.002	0.005	-0.036
UKH24 Bedford	0.012	0.026	-0.012	-0.004	0.000	0.001	0.000	-0.010	0.015	-0.003	-0.015	-0.006	-0.005	-0.001	-0.001	0.027
UKH25 Central Bedfordshire	-0.086	-0.006	-0.047	-0.007	0.000	0.000	0.000	-0.010	0.017	0.013	-0.017	-0.006	-0.009	-0.002	-0.008	-0.004
UKH31 Southend-on-Sea	-0.002	-0.001	0.003	0.000	0.001	0.002	0.000	-0.030	0.003	0.002	0.003	0.004	0.005	-0.002	0.005	0.002
UKH32 Thurrock	-0.027	-0.012	-0.003	0.000	0.000	0.002	0.000	0.002	-0.025	-0.006	0.028	-0.009	0.007	-0.001	0.000	-0.009
UKH34 Essex Haven Gateway	-0.036	-0.009	-0.013	-0.002	0.000	0.001	0.000	-0.005	-0.003	0.009	0.000	-0.008	0.002	-0.002	0.003	-0.010
UKH35 West Essex	-0.036	-0.003	-0.005	-0.004	0.000	0.002	0.000	-0.017	0.013	0.010	-0.012	-0.003	-0.002	-0.003	-0.005	-0.007
UKH36 Heart of Essex	-0.109	-0.003	-0.032	-0.004	0.000	0.002	0.000	-0.034	0.027	0.011	-0.022	-0.007	-0.005	-0.002	0.001	-0.040
UKH37 Essex Thames Gateway	-0.040	0.009	-0.011	-0.004	0.000	0.001	0.000	-0.019	-0.009	0.005	0.013	-0.006	0.003	-0.002	0.006	-0.026
UKI31 Camden and City of London	-0.046	-0.007	0.037	0.000	-0.002	0.007	0.000	-0.103	0.103	0.015	-0.090	0.001	-0.011	-0.003	-0.004	0.011
UKI32 Westminster	-0.035	0.017	0.018	0.003	-0.002	0.006	0.000	-0.101	0.098	0.022	-0.092	0.001	-0.006	0.001	-0.002	0.003

UKI33 Kensington & Chelsea and Hammersmith & Fulham	-0.021	0.009	0.029	0.001	-0.001	0.006	0.000	-0.098	0.086	0.027	-0.085	0.001	-0.007	-0.003	-0.001	0.015
UKI34 Wandsworth	0.030	0.038	0.005	-0.004	0.000	0.006	0.000	-0.089	0.088	0.019	-0.077	0.003	-0.012	-0.004	-0.008	0.065
UKI41 Hackney and Newham	-0.005	-0.003	0.018	0.003	0.000	0.006	0.000	-0.036	0.011	-0.001	-0.026	-0.001	0.003	-0.002	0.001	0.021
UKI42 Tower Hamlets	0.000	0.028	0.020	0.008	-0.003	0.006	0.000	-0.091	0.058	0.010	-0.057	-0.001	0.000	0.000	0.008	0.015
UKI43 Haringey and Islington	0.026	0.024	0.027	0.001	-0.001	0.006	0.000	-0.074	0.063	0.013	-0.066	0.002	-0.007	-0.002	0.001	0.037
UKI44 Lewisham and Southwark	-0.023	0.014	0.015	0.002	0.000	0.007	0.000	-0.053	0.044	0.002	-0.041	-0.001	-0.005	0.001	0.000	-0.007
UKI45 Lambeth	-0.021	0.029	0.023	0.002	-0.001	0.007	0.000	-0.064	0.055	0.014	-0.061	-0.001	-0.006	-0.003	-0.004	-0.009
UKI51 Bexley and Greenwich	-0.029	-0.002	-0.008	0.002	-0.001	0.005	0.000	-0.029	0.008	-0.002	0.000	-0.001	-0.005	-0.002	0.008	0.000
UKI52 Barking & Dagenham and Havering	-0.003	-0.007	0.004	0.003	-0.001	0.004	0.000	-0.015	-0.016	-0.003	0.023	-0.001	0.001	-0.003	0.006	0.000
UKI53 Redbridge and Waltham Forest	-0.053	-0.004	-0.031	0.002	0.000	0.005	0.000	-0.033	0.022	-0.005	-0.011	-0.001	-0.005	-0.003	-0.002	0.013
UKI54 Enfield	-0.008	-0.011	0.002	0.002	-0.001	0.005	0.000	-0.024	0.017	-0.002	-0.006	0.002	-0.003	-0.003	0.000	0.014
UKI61 Bromley	-0.030	0.005	-0.042	-0.002	-0.001	0.005	0.000	-0.055	0.042	0.009	-0.023	-0.001	-0.015	-0.004	0.000	0.053
UKI62 Croydon	-0.065	-0.018	-0.033	0.001	-0.001	0.006	0.000	-0.030	0.020	-0.003	0.000	0.003	-0.006	-0.002	-0.003	0.002
UKI63 Merton, Kingston upon Thames and Sutton	-0.053	0.013	-0.043	-0.001	0.000	0.005	0.000	-0.042	0.045	0.004	-0.028	0.003	-0.011	-0.003	-0.004	0.009
UKI71 Barnet	-0.078	0.000	-0.037	0.000	0.000	0.006	0.000	-0.049	0.057	0.002	-0.040	0.002	-0.012	-0.003	-0.006	0.003
UKI72 Brent	-0.044	-0.017	-0.012	0.004	-0.001	0.004	0.000	-0.019	0.008	-0.003	-0.014	0.001	0.000	-0.004	-0.007	0.014
UKI73 Ealing	-0.061	-0.001	-0.025	0.002	-0.001	0.004	0.000	-0.031	0.029	0.001	-0.032	0.001	-0.006	-0.003	-0.010	0.010
UKI74 Harrow and Hillingdon	-0.101	-0.005	-0.033	-0.001	-0.001	0.004	0.000	-0.024	0.026	-0.007	-0.007	0.001	-0.008	-0.003	0.000	-0.044
UKI75 Hounslow and Richmond upon Thames	-0.094	0.011	-0.028	-0.001	-0.002	0.005	0.000	-0.050	0.054	0.003	-0.044	0.002	-0.012	-0.003	-0.007	-0.021
UKJ11 Berkshire	-0.109	-0.006	-0.039	-0.005	-0.001	0.002	0.000	-0.037	0.041	0.001	-0.030	0.002	-0.009	-0.003	0.007	-0.032
UKJ12 Milton Keynes	-0.045	-0.007	-0.019	-0.001	-0.001	0.001	0.000	-0.025	0.018	-0.010	-0.009	-0.006	-0.003	-0.002	-0.012	0.032
UKJ13 Buckinghamshire CC	-0.146	-0.003	-0.053	-0.005	0.000	0.001	0.000	-0.031	0.044	0.012	-0.035	0.000	-0.013	-0.004	-0.008	-0.050
UKJ14 Oxfordshire	-0.073	0.004	-0.037	-0.006	0.000	0.001	0.000	-0.036	0.044	0.004	-0.036	0.005	-0.013	-0.002	-0.002	0.001
UKJ21 Brighton and Hove	-0.069	-0.005	-0.005	0.002	0.000	0.005	0.000	-0.041	0.038	0.012	-0.034	-0.005	-0.008	-0.001	-0.015	-0.012
UKJ22 East Sussex CC	-0.015	-0.005	-0.014	-0.003	0.001	0.003	0.000	-0.006	0.006	0.015	-0.011	-0.002	-0.003	-0.001	-0.008	0.013
UKJ25 West Surrey	-0.118	-0.002	-0.042	-0.005	-0.001	0.003	0.000	-0.042	0.053	0.009	-0.040	-0.001	-0.014	-0.003	-0.007	-0.028
UKJ26 East Surrey	-0.117	0.003	-0.040	-0.006	-0.001	0.004	0.000	-0.042	0.044	0.014	-0.033	-0.002	-0.013	-0.003	-0.004	-0.040
UKJ27 West Sussex (South West)	-0.011	0.003	-0.022	-0.006	0.000	0.001	0.000	0.001	0.004	0.010	-0.007	-0.002	-0.004	-0.003	-0.006	0.020

UKJ28 West Sussex (North East)	-0.089	-0.008	-0.033	-0.005	0.000	0.003	0.000	-0.017	0.017	0.004	-0.011	-0.002	-0.008	-0.002	-0.004	-0.022
UKJ31 Portsmouth	-0.040	-0.009	-0.004	0.000	0.000	0.001	0.000	0.007	-0.004	-0.001	-0.003	-0.005	0.006	0.000	-0.002	-0.027
UKJ32 Southampton	-0.055	-0.015	-0.003	0.001	-0.001	0.001	0.000	-0.003	-0.003	-0.011	0.004	-0.002	0.010	0.002	0.001	-0.036
UKJ34 Isle of Wight	0.001	-0.005	-0.005	0.000	0.000	0.000	0.000	0.019	-0.012	0.021	-0.010	-0.002	0.002	0.002	-0.005	-0.003
UKJ35 South Hampshire	-0.043	-0.007	-0.032	-0.004	0.000	-0.001	0.000	0.000	0.005	0.008	-0.006	-0.002	-0.003	-0.003	0.001	0.000
UKJ36 Central Hampshire	-0.090	-0.006	-0.033	-0.006	0.000	0.001	0.000	-0.019	0.031	0.010	-0.028	-0.002	-0.010	-0.003	-0.001	-0.023
UKJ37 North Hampshire	-0.107	-0.006	-0.039	-0.007	-0.001	0.001	0.000	-0.025	0.027	0.009	-0.024	0.000	-0.006	-0.003	-0.004	-0.030
UKJ41 Medway	-0.065	-0.009	-0.014	0.003	0.000	0.002	0.000	0.004	-0.017	0.002	0.011	-0.005	0.002	-0.001	-0.010	-0.033
UKJ43 Kent Thames Gateway	-0.063	-0.002	-0.030	-0.001	0.000	0.001	0.000	0.003	-0.011	0.002	0.007	-0.005	0.001	-0.004	-0.006	-0.018
UKJ44 East Kent	-0.007	0.002	-0.011	0.000	0.000	0.003	0.000	-0.001	-0.003	0.003	0.001	-0.005	0.002	-0.002	-0.004	0.006
UKJ45 Mid Kent	-0.058	-0.019	-0.022	-0.003	0.000	0.002	0.000	0.000	0.010	0.009	-0.014	-0.005	-0.002	-0.003	-0.008	-0.003
UKJ46 West Kent	-0.098	0.001	-0.026	-0.004	-0.001	0.003	0.000	-0.038	0.032	0.011	-0.028	-0.005	-0.008	-0.003	-0.007	-0.026
UKK11 Bristol, City of	-0.064	0.01	-0.02	0.000	0.000	0.003	0.000	-0.032	0.030	-0.006	-0.021	0.004	-0.007	0.000	-0.006	-0.017
UKK12 Bath and North East Somerset, North Somerset and South Gloucestershire	-0.085	-0.006	-0.035	-0.004	0.000	0.001	0.000	-0.014	0.019	0.002	-0.011	0.004	-0.011	-0.002	-0.007	-0.021
UKK13 Gloucestershire	-0.083	-0.009	-0.029	-0.004	0.000	-0.001	0.000	-0.008	0.011	0.006	-0.010	0.003	-0.008	-0.002	0.004	-0.036
UKK14 Swindon	-0.056	0.003	-0.024	-0.002	-0.001	-0.002	0.000	-0.011	-0.001	-0.007	0.001	0.002	0.002	-0.002	0.001	-0.014
UKK15 Wiltshire	-0.049	0.000	-0.027	-0.005	0.000	0.000	0.000	-0.005	0.013	0.016	-0.023	0.002	-0.012	-0.002	-0.006	-0.001
UKK21 Bournemouth and Poole	-0.053	-0.014	-0.012	-0.004	0.000	0.001	0.000	-0.010	0.005	0.006	-0.007	0.003	-0.002	-0.002	-0.002	-0.015
UKK22 Dorset CC	-0.094	-0.013	-0.027	-0.005	0.000	0.000	0.000	0.006	0.003	0.021	-0.020	0.003	-0.011	-0.002	-0.010	-0.040
UKK23 Somerset	-0.052	-0.004	-0.029	-0.004	0.000	-0.002	0.000	0.012	-0.006	0.013	-0.007	0.003	-0.003	-0.001	-0.007	-0.019
UKK30 Cornwall and Isles of Scilly	-0.029	-0.015	-0.013	-0.003	0.001	0.001	0.000	0.018	-0.017	0.027	-0.015	0.003	-0.004	-0.002	-0.005	-0.005
UKK41 Plymouth	0.003	-0.005	0.002	0.000	0.000	0.000	0.000	0.016	-0.019	0.004	0.011	0.005	0.004	0.008	-0.004	-0.018
UKK42 Torbay	-0.005	-0.003	-0.001	0.000	0.001	0.003	0.000	0.022	-0.024	0.014	0.005	0.005	0.002	-0.001	-0.001	-0.026
UKK43 Devon CC	-0.074	-0.008	-0.028	-0.005	0.000	0.002	0.000	0.008	-0.002	0.020	-0.017	0.005	-0.006	-0.001	-0.005	-0.037
UKL11 Isle of Anglesey	-0.020	-0.007	-0.008	-0.001	0.001	0.002	0.000	0.019	-0.011	0.019	-0.007	-0.005	0.000	-0.004	0.004	-0.023
UKL12 Gwynedd	0.004	-0.004	-0.001	-0.001	0.001	0.003	0.000	0.012	-0.011	0.020	-0.015	-0.005	-0.003	-0.004	0.005	0.007
UKL13 Conwy and Denbighshire	0.039	0.001	0.000	-0.003	0.001	0.002	0.000	0.016	-0.006	0.012	-0.004	-0.005	0.001	0.000	0.004	0.019
UKL14 South West Wales	-0.005	-0.006	-0.009	-0.001	0.001	0.002	0.000	0.017	-0.016	0.022	-0.008	-0.006	0.000	0.000	-0.005	0.004

UKL15 Central Valleys	0.084	0.014	0.023	0.003	0.000	-0.003	0.000	0.019	-0.021	-0.008	0.021	-0.006	0.006	0.002	0.000	0.033
UKL16 Gwent Valleys	0.060	0.007	0.013	0.003	0.000	-0.006	0.000	0.022	-0.027	-0.008	0.028	-0.004	0.008	0.003	-0.003	0.024
UKL17 Bridgend and Neath Port Talbot	0.100	0.023	0.023	0.001	0.000	-0.004	0.000	0.020	-0.016	-0.005	0.018	-0.004	0.003	0.000	0.002	0.038
UKL18 Swansea	-0.046	-0.012	-0.005	0.003	0.000	0.002	0.000	0.003	0.000	-0.011	0.011	-0.004	0.002	0.000	0.000	-0.035
UKL21 Monmouthshire and Newport	-0.003	0.006	-0.017	-0.002	0.000	-0.001	0.000	0.004	0.009	-0.006	-0.008	-0.004	0.000	-0.002	0.001	0.014
UKL22 Cardiff and Vale of Glamorgan	-0.011	0.00	-0.01	0.001	0.000	0.003	0.000	-0.017	0.027	-0.008	-0.010	-0.004	-0.004	0.001	-0.001	0.017
UKL23 Flintshire and Wrexham	0.020	-0.002	-0.011	-0.003	0.000	-0.008	0.000	0.016	-0.014	-0.002	0.016	-0.005	0.003	0.000	-0.001	0.033
UKL24 Powys	-0.008	-0.009	-0.016	-0.006	0.001	0.000	0.000	0.021	-0.017	0.037	-0.024	0.002	-0.001	-0.004	0.000	0.007
UKM50 Aberdeen City and Aberdeenshire	0.004	-0.001	0.004	-0.003	0.000	0.001	0.000	0.006	0.004	0.012	-0.016	0.009	-0.002	-0.002	-0.005	-0.003
UKM61 Caithness & Sutherland and Ross & Cromarty	-0.003	-0.044	-0.026	0.000	0.000	0.002	0.000	0.024	-0.022	0.032	-0.010	0.022	-0.007	-0.002	-0.002	0.029
UKM62 Inverness & Nairn and Moray, Badenoch & Strathspey	0.070	0.006	0.003	-0.004	0.000	0.001	0.000	0.030	-0.021	0.024	-0.007	0.008	0.001	-0.001	0.001	0.030
UKM63 Lochaber, Skye & Lochalsh, Arran & Cumbrae and Argyll & Bute	0.022	-0.012	0.001	-0.006	0.000	0.004	0.000	0.032	-0.030	0.035	-0.016	0.013	-0.002	-0.001	0.003	0.001
UKM64 Na h-Eileanan Siar (Western Isles)	0.006	-0.016	-0.033	-0.005	0.000	0.004	0.000	0.022	-0.018	0.027	-0.007	0.019	-0.005	0.000	-0.004	0.022
UKM71 Angus and Dundee City	0.050	0.005	0.021	0.002	0.000	0.001	0.000	0.017	-0.014	0.002	0.006	0.007	0.004	0.000	0.008	-0.009
UKM72 Clackmannanshire and Fife	0.036	0.005	0.000	-0.001	0.000	-0.001	0.000	0.007	-0.011	0.005	0.006	0.002	-0.001	-0.002	0.008	0.018
UKM73 East Lothian and Midlothian	0.012	0.013	0.000	-0.004	0.000	0.004	0.000	-0.004	-0.011	0.007	0.008	0.015	-0.004	0.000	0.002	-0.014
UKM75 Edinburgh, City of	-0.017	-0.002	0.001	-0.003	-0.001	0.005	0.000	-0.047	0.049	-0.007	-0.034	0.015	-0.008	0.003	0.001	0.011
UKM76 Falkirk	0.075	0.011	0.026	-0.001	0.000	-0.002	0.000	0.020	-0.021	0.004	0.016	0.004	-0.001	0.002	0.009	0.010
UKM77 Perth & Kinross and Stirling	-0.004	0.001	-0.010	-0.003	0.000	0.003	0.000	0.010	0.007	0.013	-0.022	0.011	-0.008	0.001	0.002	-0.008
UKM78 West Lothian	0.072	0.015	0.008	-0.002	0.000	-0.002	0.000	0.001	-0.016	-0.006	0.019	0.005	-0.002	0.001	0.005	0.047
UKM81 East Dunbartonshire, West Dunbartonshire and Helensburgh & Lomond	0.059	0.009	0.021	-0.002	0.000	0.002	0.000	-0.001	0.008	0.006	-0.002	0.009	-0.009	0.002	0.009	0.006
UKM82 Glasgow City	0.068	0.00	0.04	0.004	0.000	0.003	0.000	-0.005	0.000	-0.011	0.002	0.010	0.005	0.007	0.002	0.005
UKM83 Inverclyde, East Renfrewshire and Renfrewshire	0.071	0.006	0.025	0.000	0.000	0.001	0.000	0.001	0.006	-0.004	0.007	0.005	-0.007	0.005	0.000	0.027

UKM84 North Lanarkshire	0.111	0.020	0.040	0.000	0.000	0.000	0.000	0.019	-0.025	-0.009	0.032	-0.004	0.001	0.000	0.006	0.031
UKM91 Scottish Borders	0.040	-0.001	0.012	-0.003	0.000	-0.001	0.000	0.021	-0.010	0.019	-0.013	0.014	-0.003	-0.001	-0.001	0.006
UKM92 Dumfries & Galloway	0.091	0.008	0.014	-0.004	0.000	0.000	0.000	0.037	-0.033	0.014	0.007	0.007	-0.004	-0.002	-0.009	0.056
UKM93 East Ayrshire and North Ayrshire mainland	0.103	0.017	0.034	0.007	0.000	-0.001	0.000	0.028	-0.024	0.004	0.018	0.006	0.003	0.004	0.010	-0.002
UKM94 South Ayrshire	0.076	0.020	0.024	-0.001	0.000	0.000	0.000	0.024	-0.004	0.009	-0.003	0.007	-0.004	0.004	0.011	-0.010
UKM95 South Lanarkshire	0.055	0.014	0.014	-0.003	0.000	0.000	0.000	0.011	-0.006	0.001	0.015	0.001	-0.005	0.000	0.002	0.009