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Authors: Jennifer Roberts and Karl Taylor

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NEW EVIDENCE ON DISABILITY BENEFIT CLAIMS IN THE UK: THE ROLE OF HEALTH AND THE LOCAL LABOUR MARKET

Jennifer Roberts[#]
Department of Economics
University of Sheffield
j.r.roberts@sheffield.ac.uk
[#] *Corresponding author*

Karl Taylor
Department of Economics
University of Sheffield; and
IZA Bonn
k.b.taylor@sheffield.ac.uk

Abstract

During the 1980s and 1990s there was a steep rise in disability benefit claims in the UK, especially among older male workers, and the debate centred on the relative generosity of these benefits as well as the effects of deindustrialisation and job destruction. Since that time the disability benefit system has been subject to a series of reforms all largely aimed at reducing the number of claims and targeting benefits more closely to those with the greatest health need. At the same time the UK labour market has also evolved and in particular now has an historically low level of unemployment, accompanied by falling real earnings. In this paper we use individual longitudinal data from 2009 to 2018 in a dynamic panel framework to explore the relative importance of health status, benefit generosity and local labour market conditions for disability benefit claims in the modern UK labour market. We focus particularly on spatial variation in claims, and find that, in line with older evidence, while health status is clearly important, geographic variation in labour market conditions and benefit generosity still influence the propensity to claim those disability benefits that are conditional on not working. In addition, local benefit work capability re-assessment rates, which reflect the stringency that new procedures are being implemented locally, are an important factor. The average effects also mask important heterogeneity by sex, age, education level, income and across regions.

JEL classification: I12; I38; J23.

Keywords: health; disability; employment support allowance; local labour markets.

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1. INTRODUCTION

During the 1980s and 1990s there was a steep rise in disability claims in the UK, especially among older male workers. It is well known that this increase was not fully explained by the deterioration in the health of the working age population, and that changes in labour demand conditions and characteristics of the benefits themselves were also important factors (McVicar, 2008). The debate at the time centred on the relative generosity of these health related benefits compared to standard unemployment benefits, as well as the effects of deindustrialisation and job destruction. Since that time the disability benefit system has been subject to a series of reforms all largely aimed at reducing the number of claims overall and targeting benefits more closely to those with the greatest health need.[1] At the same time the UK labour market has also evolved and is now characterised by a historically low level of unemployment, which is accompanied by falling real earnings (Costa and Machin, 2017).[2] Furthermore, the health of the working age population has continued to deteriorate. The proportion of the working age population classified as disabled, according to the Disability Discrimination Act 1995, rose from 15% in 1998 to 20% in 2016. Those reporting any kind of physical health problem increased from 21% to 26%, while those reporting a mental health problem rose from 4% to 10%.[3]

Economy wide trends hide important heterogeneity both on the demand and supply side, and in particular there is a large amount of variation in both individual circumstances and labour market conditions across the UK. In 2016 the proportion of the working age population claiming Employment Support Allowance (ESA), the UK equivalent of Disability Insurance (DI) in the US, was lowest in the South East of England at 4.4%, and highest in the North East (7.9%) and Wales

[1] Recently, Low and Pistaferri (2019) have reviewed the literature on disability insurance in the US and UK and find that research has tended to over-emphasise the extent of false claims, rather than focus on how to improve insurance targeting to alleviate false rejections of genuine claimants. They find that the latter is the bigger problem, although most of their empirical evidence comes from the US.

[2] Median UK real wages fell by 5% from 2008 to 2014, with a slight recovery since then but smaller than in the majority of OECD countries (Costa and Machin, 2017).

[3] The proportion reporting both mental and physical health problems also increased from 3% to 6% (data from the Quarterly Labour Force Survey accessed via the UK Data Service).

(8.2%).[4] This pattern is mirrored by the unemployment rate, which in 1998 ranged from 4.4% in the South East to 8% in the North East.[5] In 2016 despite falling levels of unemployment overall the spatial pattern was very similar and there was little sign of any convergence with rates of 4% in the South East and 7.4% in the North East.[6] Wages also follow a similar pattern; median annual gross earnings of full-time workers in the South East in 2016 were £30,741, compared to £25,660 in the North East.[7] Similar geographic variation is evident in the health status of the population. In 2011 the proportion of working age people reporting themselves to be in *very good* (*very bad*) health (as opposed to *good, fair,* or *bad*) varied from 44% (1.7%) in the North East to 50% (1.0%) in the South East. 2.7% of working age people in the South East say that their day-to-day activities are limited a lot by their health, compared to 5.1% in the North East.[8]

Layered on these distinct geographic inequalities in health and labour market circumstances, there is also important heterogeneity across individual claimants, which is reflected in differences by age, sex, education level and type of health problem. For example, whereas the growth in disability rolls during the 1980s and 1990s was largely among older men, today younger men with lower education levels are twice as likely to receive disability benefits as older men who have a high level of education; and the likelihood of claiming these benefits is now much better predicted by education level than by age. Also claimant rates of women are catching up with those of men, partly as a result of converging participation rates between the sexes (Emmerson et al., 2017). In terms of health status, in contrast to the dominance of musculoskeletal problems in the 1980s and 1990s, mental health problems are now the most important reason for claiming; 42% of claimants in 2016 were classified as having a 'mental or behavioural disorder', compared to only 14% with musculoskeletal problems.[9]

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[4] Rates calculated from the claimant count and population estimates accessed via NOMIS (www.nomisweb.co.uk), which is a service provided by the Office for National Statistics (ONS) containing official labour market statistics.
[5] Robson (2001) considered regional differences in the competiveness of unemployed job-seekers and the rate of outflows from unemployment as an explanation for geographic disparities in UK unemployment rates.
[6] Data from the Labour Force Survey accessed via NOMIS (www.nomisweb.co.uk).
[7] Data from the Annual Survey of Hours and Earnings accessed via NOMIS (www.nomisweb.co.uk).
[8] Data from the 2011 Census accessed via NOMIS (www.nomisweb.co.uk).
[9] Data from DWP, www.gov.uk/government/statistics/dwp-statistical-summaries-2017 (Supporting Tables).

Our aim in this paper is to explore the relative importance of health status, benefit generosity and local labour market opportunities for disability benefit claims in the modern UK labour market. We make the following main contributions to the literature. Firstly, we use individual longitudinal data from 2009 to 2018 in a dynamic panel framework, which is able to capture the strong persistence in disability benefit claims (e.g. Berthoud, 2004; Anyadike-Danes and McVicar, 2008).[10] Secondly, we focus on geographic variation in claims because this is an important and persistent feature of the UK context but it is under-researched compared to the amount of evidence on the growth of disability benefit rolls over time (McVicar, 2006). Thirdly, unlike the majority of existing studies which simply estimate average effects for the whole economy, we explore the important role of heterogeneity by considering variation in the results by individual characteristics such as gender, age, qualifications, income and type of health problem. Fourthly, we use a broader set of health measures than has been used in the literature to date. We do not rely on simple self-assessed health measures, which are subject to multiple reporting biases (Bound and Burkhauser, 1999). Instead, we use a number of different measures of health to more accurately control for underlying health status, and explore the effects of heterogeneity across conditions. Finally, we update the available evidence for the UK, which is a key contribution given the substantial economic changes brought about by the Great Recession (e.g. see Blundell et al., 2014), the ongoing reforms to the disability benefit system, (e.g. see Banks et al., 2015), and the scale of recent changes in the factors determining disability benefit claims, both on the demand and the supply side.

Our results show that while health status is clearly important, geographic variation in labour market conditions and benefit generosity still influence the propensity to claim those disability benefits that are conditional on not working. In addition, local benefit work capability re-assessment

[10] Berthoud (2004) calculated exit rates from invalidity benefits over the period 1999 to 2002 and found that long term claimants have low prospects of ever leaving Incapacity Benefit (IB). His estimates of exit rates were 12% at the end of month one, falling to 9% for month two, 2% for month twelve and only 1% at month 30. This is supported by the qualitative work of Kemp and Davidson (2010) who document three processes associated with duration on IB. First, labour market engagement declines; second, stated barriers to employment increase; and, third, the likelihood of moving off benefit reduces. Similarly, Beatty et al. (2010) find that optimism about ever working again declines with duration on an IB.

rates, which reflect the speed at which the new stricter assessment procedures are being implemented locally, are an important factor, and we find that higher benefit re-assessment rates lower the propensity to claim. These average effects also mask important heterogeneity by sex, age, education level, income and between regions.

2. BACKGROUND AND MOTIVATION

Spending on disability benefits in the UK as a share of GDP has been decreasing since the mid-1990s, however, the numbers in receipt of benefits remains high by historical standards. Around 2.3 million people received these benefits in 2013, which was higher than in any year prior to the mid-1990s, and the government was expected to spend £24 billion on these benefits in 2016-17 (Emmerson et al., 2017; Banks et al., 2015).[11] The UK is not alone in struggling with growing disability benefit rolls. Public spending on disability benefits stands at 2% of GDP on average across the OECD, rising to as much as 5% in countries such as Norway, the Netherlands and Sweden. Around 6% of the working-age population in the OECD rely on disability benefits, and this figure is as high as 12% in some countries in the north and east of Europe (OECD, 2010).

Around 5.5 million people of working age in the UK have some kind of long term illness or disability, a trend which has been increasing steadily over time. Further, there is a large 'disability employment gap', with only 44% of people with a disability in work, compared to 87% of individuals who do not have a disability. This gap is even larger if we look solely at people with mental health problems; their employment rate stands at only 35% (Oakley, 2016). The current government have pledged to substantially narrow this disability employment gap and reduce the disability benefits caseload.[12] Partly this is a response to recessionary pressures and the need to limit the fiscal burden of social security provision. However, it is also recognised that work is key to reducing poverty and

[11] Actual expenditure in 2016-17 was £29 billion (www.gov.uk/government/collections/benefit-expenditure-tables).
[12] The Improving Lives: … Green Paper (DWP, 2016) pledged to halve the disability employment gap; this aim was revised in the White Paper (DWP, 2017) to trying to get 1 million more disabled people into work over the next 10 years; increasing the number of people with a disability who are working from 3.5 million to 4.5 million.

social exclusion, and that 'good work' can also have positive impacts on health and wellbeing (Waddell and Burton, 2006).

An important issue in relation to disability benefits claims is the extent to which these claims are purely a result of individual health status (a supply side issue), or whether they are also a response to labour market conditions and to the relative attractiveness of benefits (which both relate to the demand side).[13] The policy tools required to reduce the disability benefits burden are very different in these two circumstances. Compared to the large amount of evidence that has been generated on the growth of disability claims during the latter part of the twentieth century, there are only a small number of studies that consider geographic variation in these claims. McVicar (2006) shows that at the beginning of the 2000s the UK displayed a distinct regional pattern where working-age men and women in the 'North' were considerably more likely to be claiming disability benefits than those in the 'South'. As the statistics we presented in the introduction seem to suggest, these patterns still appear to be true today. The map shown in Figure 1 reveals how the proportion of disability benefit claimants varies across Local Authority Districts (LADs), where claimant rates are typically lower in the South East and higher in the North, Wales and parts of the Midlands.

McVicar (2006) provides an excellent review of the potential determinants of this geographic variation which we rely on here, providing updated evidence where relevant. It is worth stressing here that most of the econometric studies in this area are quite old, using data only up to the early 1990s. Furthermore, we can find no recent evidence that has systematically explored disability benefit take-up for different types of individuals; hence a primary aim of this paper is to update this evidence base.

The first possible contributory factor is spatial variation in health, which might be partly a result of variation in demographic and socio-economic factors, largely due to the age distribution of the local population and the incidence of deprivation (O'Leary et al., 2005; Nolan and Fitzroy, 2003;

[13] Whilst these benefits support those of employable age who are unable to work, there is evidence that disability benefits may actually contribute to low participation and employment rates among people with disability (e.g. Autor and Duggan, 2003; Jones and McVicar, 2017). Milligan and Schirle (2019) refer to the 'push' of weak labour markets and the 'pull' of more generous benefits in their exploration of disability insurance claims in the US and Canada. Furthermore, while not exploring health explicitly, Brewer et al. (2012) have carried out similar analysis for the UK in relation to the introduction of Universal Credit (UC) and its potential upon work incentives.

Beatty and Fothergill, 1999; Molho, 1989; 1991), and partly due to regional concentrations of the types of heavy industry associated with high levels of occupational ill-health (Beatty et al., 2000; Beatty and Fothergill, 1996; 2002). More recently, increased prevalence (or at least increased reporting) of mental health conditions mean that spatial variation in these type of health problems may be particularly important in determining variation in benefit claims. The map in Figure 2 illustrates the geographic variation in the number of health problems reported by LAD, where problems are found to be lower on average in the South East and more prevalent in Scotland, South Wales, Cornwall and Lincolnshire.

Secondly, older evidence suggests that the geographic variation in disability benefit claims was greater than that predicted by variation in health and disability alone, and the consensus in the literature was that local labour market conditions were the primary driving force behind this (Disney and Webb, 1991; Beatty and Fothergill, 1999). A number of studies have demonstrated the significance of local unemployment rates in determining the probability of disability benefit receipt (Disney and Webb, 1991; Holmes and Lynch, 1990; Lynch, 1991). Beatty et al. (2000) provide some explanation for this arguing that in areas of low labour demand, many of those with underlying health problems who enter unemployment soon became disenchanted with job search, which leads to a further 'benefit shift' from unemployment onto disability benefits. Beatty and Fothergill (2005) showed that the number of people claiming incapacity benefits was greater in the old industrial areas characterised by high unemployment, slower economic growth and higher socioeconomic deprivation; indeed they argue that these disability benefit claims were to some extent masking unemployment.[14]

More recently, while not studying disability claims directly, Little (2009) employs a decomposition method and Labour Force Survey data from 2003 to 2005 to assess the relative

[14] The same authors have studied the labour market in the UK coalfields in the wake of pit closures, in disadvantaged rural areas and in seaside towns, to also illustrate the 'diversion' from unemployment to sickness benefits (Beatty and Fothergill, 1996; 1997; 2004). Fothergill (2001) also describes long-term sickness and disability as one of the most important sources of hidden unemployment in Britain. Similarly, in the context of the US economy Black et al. (2002) consider the impact of the boom and bust in the coal mining industry during the 1970s and 1980s exploring how this influenced participation in disability insurance programs.

importance of ‘people’ and ‘place’ factors in explaining regional disparities in economic activity and inactivity. He finds that demographic differences accounted for only a small fraction of spatial variation in recorded sickness. He draws on more descriptive survey evidence to back his claim that a mismatch between labour demand and supply is the major cause of the variation. Recent evidence presented by Webster et al. (2010) shows that all of the areas that saw high levels of claims in the 1980s and 1990s have seen large decreases in claimants in the early 2000s; and they show that in Glasgow for example, this has resulted more from a strengthening of the local labour market than from any national policy initiatives. McVicar (2013) presents further evidence of some convergence in claimant rates at the Local Authority level between 1999 and 2008. His area based analysis reveals that differences in the strength of local labour markets was the main factor explaining the variation in claims, but that differences in self-reported disability also played a role. The map in Figure 3 shows how unemployment rates vary across the local authority district, where unemployment is typically higher in the North and Midlands, and parts of South Wales.

While hidden unemployment may have been an important explanation during the rapid deindustrialization of the 1980s and early 1990s, especially in the North of Britain, it is unlikely to have been as important a factor more recently. The late 1990s through to the early 2000s was a period of sustained labour market growth and McVicar (2013) argues that this was responsible for some of the spatial convergence in rates that he identified. However, he also points out that, since the Great Recession ended this period of sustained labour market growth, any further convergence may be halted.[15] The recession has impacted differently on different parts of the labour market. Coulter (2016) has analysed sectoral effects during and after the recession, concluding that low paid public sector jobs saw the greatest losses, and that most growth in employment since then has been in self-employment or low-paid and insecure private sector jobs (also see Blundell et al., 2014). ONS figures

[15] Anyadike-Danes (2010) also finds only limited evidence for any regional convergence in disability claims over the period 2000 and 2007.

suggest that in terms of overall unemployment the West Midlands was the region worst hit by the recession and the smallest increases in unemployment were in the South East.

Ritchie et al. (1993) also pointed to the role of General Practitioners (GPs) in exacerbating the effects of local labour demand conditions, since they may be more likely to deem individuals as eligible for benefits when there are limited opportunities in local labour markets. We would expect this influence to have weakened with successive reforms which have replaced assessments by recipients own GP with those carried out by Benefits Agency independent doctors, and most recently a Work Capabilities Assessment (WCA) carried out by a private sector external provider. Grover and Piggott (2010) argue that this contracting out of WCA was partly to address the concern that GP assessments were influenced by wider economic and social factors, and not simply by the functional capabilities of the individual claimants (see also Hiscock and Ritchie, 2001). While the US literature has pointed to the importance of screening procedures in explaining both state level variation in claims and the rapid growth over time, there is no clear evidence for the UK (McVicar, 2006). While ESA is governed by national policy it is implemented locally so there is still potential for local variation in procedures to play a role in exacerbating the geographic variation in claims. In the empirical analysis that follows we follow Barr et al. (2016) and consider local variation in WCA re-assessment rates as a proxy for the stringency by which new procedures are being implemented locally. The programme of re-assessment was initiated in 2010 with the aim of eventually assessing all existing claimants of out-of-work disability benefits via a WCA. Figure 4 shows how the benefit re-assessment rate varies across the UK. This is the number of WCA re-assessments carried out as proportion of the working age population. Clearly, this rate will vary with the number of claimants and local area deprivation, but as the map shows the variability in the re-assessment rate is distinct from the other local labour market variables we have considered so far. For example, while parts of North Norfolk and East Anglia have among the highest proportion of benefit claimants, they have among the lowest rates of re-assessment.

Thirdly, the relative attractiveness of disability benefits may be an explanation for the geographic variation in claims. While benefit rates are set nationally, regional wages vary substantially so the replacement rate also varies; in lower wage areas disability benefits are relatively more attractive. Of course they are also relatively more attractive to those workers who can only command low wages due to their individual human capital endowments, but to date there is very little evidence on this. Again some older evidence supports the hypothesis of the importance of local replacement rates (Holmes and Lynch, 1990: Lynch, 1991; Disney and Webb, 1991). More recently Faggio and Nickell (2003) find a strong negative relationship between regional wages and prime age male inactivity. In recent years low levels of unemployment have been accompanied by falling real wages which may make disability benefits more attractive for those who cannot find work. However, real wages for lower paid workers have risen due to recent initiatives to 'make work pay', including increases in the National Minimum Wage, the introduction of the National Living Wage and Working Tax Credit, which all mean lower replacement ratios especially for workers towards the bottom end of the wage distribution. Figure 5 shows the variation in benefit replacement rates across LADs (as a percentage of the local median wage).

3. HEALTH RELATED BENEFITS IN THE UK

During the period of our analysis there were two main types of benefits available to working age people in the UK with a disability or health problem. Firstly, benefits such as the Disability Living Allowance (DLA) (now replaced with Personal Independence Payments (PIP)), that are designed to meet the increased costs associated with having a disability. DLA was introduced in 1992 for disabled individuals aged under 65 to cover the cost of personal care and/or mobility needs due to a disability. This was replaced in the Welfare Reform Act of 2012 with PIP which could be claimed by those of working age. PIP is non-means tested, but involves regular work-capability assessments (see below); receipt of PIP however is not conditional on not working.[16] Secondly, incapacity benefits, such as the

[16] Individuals can work (or be unemployed but deemed capable of work) and still claim PIP. However work capability may reduce the amount of PIP that individuals are entitled to because this is interpreted as reflecting a greater degree of functioning, hence a lower level of disability.

Employment Support Allowance (ESA), which provide welfare support to those who cannot secure employment due to their health. About two-thirds of government spending on disability benefits goes on these latter incapacity benefits; and they are the focus of this paper. ESA was introduced in 2008 to replace Incapacity Benefit (IB).[17] IB itself was introduced in 1995 to replace Invalidity Benefit (IVB). IVB was considered a generous benefit and it has been associated with a steep rise in disability claims during the 1990s. Bell and Smith (2004) illustrate the financial attractiveness of IVB relative to unemployment benefits, especially for older male workers, who were most at risk of job loss from the decline in the traditional manufacturing industries.

In January 2006 the UK government set the ambitious target of reducing the number of IB claimants by one million (around 40%) within the next decade (DWP, 2006).[18] IB began to be phased out following the Welfare Reform Act 2007, and ESA replaced it for new claims from 2008. ESA was designed to have more stringent eligibility criteria than either IVB or IB. Claims for ESA are assessed using a WCA, which is carried out by an external provider and determines whether or not the claimant can carry out a set of physical and cognitive activities, based on a list of Activities of Daily Living questions.[19] The process of moving existing claimants onto ESA began in October 2010 and was planned to be completed by April 2014, but this deadline was not met due to delays in the WCA process that led the government to terminate the contract with the original external provider (Hood and Keiller, 2013).[20]

[17] ESA itself is now in the process of being replaced by Universal Credit (UC), which will integrate six means-tested benefits for working-age families. The UC rollout has been subject to a number of delays and the latest government advice suggests that ESA claimants will not start to move to UC until 2020 at the earliest.
[18] We now know that the claimant count fell by less than 300,000 over that period (Emmerson et al., 2017).
[19] ESA claimants are placed either in the *work related activity group,* who are expected to prepare for eventual return to work (they receive a lower rate of support and attend regular interviews at the job centre), or the *support group* who receive a higher rate of ESA and are not subject to conditionality. In 2015-16 the support group was 3.4 times larger than the work related activity group, which was much greater than planned. In 2012 the Office for Budget Responsibility (OBR) forecast that by 2015-16 the support groups would be a quarter the size of the work related activity group (Emmerson et al., 2017).
[20] In Autumn 2012 the OBR assumed that, as the replacement of IB with ESA continued, the caseload would fall by 21% by 2015-16 compared with its level at the start of the parliament. However, the caseload actually only fell by 4% over this period. Spending on these benefits was forecast to be 27% lower in 2015-16 than in 2010-11; but instead it was 6% higher (Emmerson et al., 2017). In our data the proportion of individuals on ESA increases from 0.7% in 2010 to 5% in 2018, while the proportion on IB falls from 4.2% to 0.4% over the same period. (Transitions between benefits over time are shown in Table 1).

4. DATA AND METHODOLOGY

We use the first nine waves of *Understanding Society* – the UK Household Longitudinal Survey (UKHLS), University of Essex (2019); a nationally representative longitudinal study of the UK population which started in 2009 as the successor to the British Household Panel Survey. The UKHLS contains detailed information on economic and social-demographic characteristics and by special license can be merged to detailed information at the local area level. In the first wave of the UKHLS, over 50,000 individuals were interviewed over the period 2009 to 2011 and correspondingly in the latest wave available (at the time of writing), wave 9, around 36,055 individuals were interviewed between 2017 and 2019. The sample we focus on is 35,116 individuals who are currently of working age (i.e. 16 to 65) and are either in paid employment, unemployed, or long-term sick or disabled, who resided in same residence in each wave (i.e. we exclude movers – around 7% of individuals). These individuals are observed 6 times on average yielding an unbalanced panel of 130,363 observations. The UKHLS has information on whether the individual claimed benefits, specifically: Incapacity Benefits (IB); Employment and Support Allowance (ESA); Personal Independence Payments (PIP); or Disability Living Allowance (DLA). We have detailed information on the Local Authority District (LAD) in which the individual resides, which allows us to merge in proxies for local labour market conditions.[21] Table 1 shows a transitions matrix of benefit status. Clearly, most of the sample are not in receipt of health related benefits, at around 92%. The lead diagonal shows that the majority of individuals remain in the same state as the previous period, where for example approximately 72% remain on ESA across waves. Moreover, as expected most individuals on IB in the previous wave transition onto ESA or into claiming no benefits.[22] In our analysis we model both ESA alone and either ESA or IB to take account of this transition process. We also model the probability of claiming only PIP/DLA benefits. PIP/DLA claims are not dependent on working status, and an individual may

[21] There are 420 LADs in the UKHLS.

[22] The small percentage (2.34%) who report ESA at $t-1$ and IB at t is likely to be a result of misreporting, since this is not possible as the recipients were being gradually moved from IB to ESA over this period. We treat these observations as reporting error and recode them as ESA claimants. Note that the results which follow are not sensitive to either keeping the originally indicated benefit state as IB or recoding to having coming off benefits completely.

be in receipt of both ESA and PIP/DLA. In our data 49% claim both ESA and PIP/DLA, 51% are ESA claimants only and 68% claim PIP/DLA only.

Defining $i = 1,2, \dots ,35,116$ and $t = 2,3 \dots ,9$ to denote the individual and the time period respectively,[23] we model the probability of being on benefits (b_{it}) by type, i.e.: ESA; ESA or IB; and PIP or DLA, in a dynamic framework as follows which is a correlated random effects approach with the incorporation of a lagged dependent variable, see Wooldridge (2005, 2010):

$$b_{it} = 1\left(\gamma b_{it-1} + \boldsymbol{X}_{it}'\boldsymbol{\beta} + \sum_{j=1}^{J}\sum_{g=1}^{G}\phi_j\{H_{jit} \times S_{git}\} + \sum_{k=1}^{3}\sum_{g=1}^{G}\psi_k\{U_{krt-1} \times S_{git}\} + \theta_t \right.$$

$$\left. + \alpha_i + \epsilon_{it} > 0\right) = 1(\boldsymbol{Z}_{it}{}'\boldsymbol{\delta} + \theta_t + \alpha_i + \epsilon_{it} > 0) \quad \text{(1A)}$$

$$\alpha_i = \alpha_0 + \alpha_1 b_{i0} + \overline{\boldsymbol{Z}}_i'\boldsymbol{\pi} + \omega_i \quad \text{(1B)}$$

A dynamic specification is appropriate here given the strong persistence in disability benefit claims found in the literature (e.g. Berthoud, 2004). We condition upon a set of covariates, $\boldsymbol{X}_{it}$, proxies of the individuals health, H_{jit}, where ($j = 1,2, \dots , J$) denotes the number of health states, and the state of the local labour market and benefit system in the previous year, U_{krt-1}. The latter controls are defined across three variables $k = 1,2,3$ specifically the local unemployment rate, the local disability benefit replacement rate (level of benefits as a percentage of the local median wage) and the benefit re-assessment rate (total number of cases re-assessed by WCA as a percentage of the local population aged 16-65; see Barr et al, 2016), with each defined at the LAD level ($r = 1,2, \dots ,420$).[24] We also interact the key covariates with binary indicators, S_{git}, defining a number of states, e.g. gender (where $G = 2$) or age groups (where $G = 5$), to investigate whether there are heterogeneous effects of health status and/or local labour markets on benefit receipt. In specifications where heterogeneity is not incorporated, $S_{it} = 1 \; \forall \; i$.

[23] The first time that the individual is observed in the panel is lost as this is used to specify the initial condition, see below. Also due to the inclusion of a lagged dependent variable the estimation sample is based upon 26,939 individuals (N) and total observations of 95,247 (NT).

[24] The local labour market data are obtained from NOMIS (www.nomisweb.co.uk). Information on benefit re-assessment is obtained from Stat-Xplore an online tool from the DWP (https://stat-xplore.dwp.gov.uk/webapi/jsf/login.xhtml).

If benefit entitlement is solely determined by health status then we expect $\psi_k = 0$. However, we argue that while this should be true for DLA/PIP claims which are not dependent on employment status, it is unlikely to be the case for ESA/IB claims. ESA and IB are not available to working people and claimant rates are likely to respond to labour market conditions and the relative attractiveness of benefits, as well as individual health status.

Equation (1A) is estimated as a random effects dynamic probit model, where the correlation between the fixed effect, α_i, and the lagged dependent variable, b_{it-1}, yields an endogeneity problem which will result in inconsistent estimates. We follow Wooldridge (2005) and specify the fixed effect in equation (1A) conditional upon the initial state, b_{i0}, i.e. whether the individual is on disability benefits when first observed in the panel, and the group means of individual level time varying covariates, including health, $\overline{\boldsymbol{Z}}_i \ni (\overline{\boldsymbol{X}}_i, \overline{H}_{ji})$, as shown in equation (1B). Substitution of equation (1B) into (1A) yields an augmented correlated random effects model where the parameters approximate those of a fixed effects estimator. State dependence in terms of the statistical significance of b_{it-1} and the magnitude of γ as well as the importance of unobserved heterogeneity, as given by $\rho = [\sigma_\alpha^2/(\sigma_\alpha^2 + \sigma_\epsilon^2)]$, is investigated by estimating equations (1A and 1B). In terms of our key variables of interest the focus is on the health parameters and the influence of the local labour market on the probability of benefit receipt, i.e. the ϕ_j and ψ_k, in terms of statistical significance, sign, and magnitude. In particular we explore the relative importance of the individuals' current health status and the state of the prevailing local labour market for the likelihood of receiving benefits, i.e. $\phi_j > \psi_k$ or vice versa. Note also that in further analysis reported below we adopt a GMM approach which relaxes the assumptions that health is exogenous and labour market conditions are pre-determined, and instead allows for the likelihood that making a benefit claim, local labour conditions and an individuals' health are all potentially jointly determined.

In the vector $\boldsymbol{X}_{it}$ we control for the following individual and household characteristics: gender; ethnicity; whether the individual is an immigrant; the age of the individual, specifically binary indicators for whether aged 16-24, aged 25-34, aged 35-44 or aged 45-54, with those aged 55-65 as the reference group; the number of individuals in the household (excluding the respondent); the number of children in the household aged 0-2, aged 3-4, aged 5-11 and aged 12-15; highest educational attainment, specifically whether a degree (undergraduate or postgraduate level), any other higher level qualification (e.g. teaching or nursing), A level, AS level, GCSE, any other qualification, with no education as the omitted category; whether married or cohabiting; housing tenure, i.e. whether owned outright, on a mortgage with equity, on a mortgage but in negative equity (where the remaining mortgage amount exceeds the estimated value of the house), with renting as the reference group; the natural logarithm of real equivalized monthly income in 2009 prices; whether the individual lives in an urban area; and government office region indicators with London as the omitted region. Time fixed effects θ_t are also included. Summary statistics for the covariates in $\boldsymbol{X}_{it}$ are given in Table 2, for the estimation sample where: just under half the sample are male; 32% are aged 45-54; 26% have a degree as their highest educational qualification; the majority of households own their own home via a mortgage with equity, although 3.5% have negative equity; the mean equivalized income is 7.59 log units i.e. £2,339 per month; and 81% live in an urban area. The unemployment rate, replacement ratio and benefit re-assessments rate all display large ranges, reflecting the variation shown in Figures 3, 4 and 5. For example, the replacement ratio is typically found to be higher in Wales, Cornwall, the East of England and Scotland; whilst the benefit re-assessment rate is higher in Wales and Northern England and lower in the South East. In the empirical analysis the local labour market covariates are included as natural logarithms.

In terms of individuals health state, H_{jit}, this is defined in a number of alternative ways. Firstly, following Banks et al., (2015) we construct three binary indicators ($J = 3$) for whether health problems are mild, moderate or severe, based upon answers to questions related to various Activities of Daily Living (ADL): walking; sitting; standing; climbing stairs; lifting a weight; picking up a 5p coin etc.; as well as eyesight; incontinence; and stress. These ADL questions are very similar to the ones that are used in the WCA. The omitted category is no health problem. Secondly, in an alternative specification we condition on twelve health indicators ($J = 12$) reflecting the type of ADL problem that the individual has, specifically whether problems with one or more of the following: mobility; lifting or carrying; manual dexterity; continence; hearing; sight; communication or speech; memory or ability to concentrate, learn or understand; recognising when in physical danger; physical coordination; personal care; any other type of health problem. The omitted category is no health problem. Thirdly, rather than conditioning upon the type of ADL problem we control for the number of problems reported, ($J = 1$). Fourthly, we consider the number of specific health conditions reported by the individual, ($J = 1$), constructed from a count of the following: asthma; arthritis; diabetes; high blood pressure; depression; and any other condition. Finally, we include two scores for physical and mental health, ($J = 2$). These are derived from the Short Form 12 (SF-12) generic health instrument, a multidimensional measure of health comprising twelve questions relating to issues such as pain, physical functioning, social functioning and mental health (Ware et al., 1995). The mental and physical health sub-scales convert valid answers to the twelve original questions into a single functioning score, resulting in a continuous scale with a range of 0 (low functioning) to 100 (high functioning). Table 3 provides summary statistics of each of the alternative health measures. Approximately 6% of individuals have mild ADL problems compared to just over 1.6% who have severe problems, just under 17% have an ADL problem (with the mean number of health problems at 0.4) with the most prevalent been lifting (mobility) at 9.6% (8.9%), and 15% report a specific health condition (with the mean number of health conditions equal to 0.2).

5. RESULTS

Each of the tables which follow show the results of estimating correlated random effects dynamic probit models (equations 1A and 1B) for the different types of benefit claims. All tables comprise three columns containing average marginal effects and robust t-statistics in parenthesis for the probability of receiving: (i) ESA; (ii) ESA or IB; and (iii) PIP or DLA, respectively. Table 4 reports full results for all variables (excluding region), with the final rows of the table showing the marginal effects for the lagged dependent variable, local labour market effects (defined at the LAD level) i.e.: unemployment rate, benefits replacement ratio and benefit re-assessment rate (all lagged by one year), and lastly, individual health defined in line with Banks et al. (2015) as the presence of mild, moderate or severe health problems according to the ADL questions. As expected in all three columns health is a key determinant of disability benefit claims, with a clear gradient across mild, moderate and severe problems; the more severe the health problem the greater the probability of making a health related benefit claim. Specifically, having severe health problems increases the probability of claiming ESA by around 2.5 percentage points. For ESA, a higher local unemployment rate increases the propensity to claim whilst conversely a higher local benefit re-assessment rate reduces the propensity to claim benefits. For example, a doubling of the unemployment rate (benefit re-assessment rate) would increase (decrease) the probability of making an ESA claim by 0.5 (0.8) percentage points. In contrast, as expected, local labour market effects have no association with the probability of making PIP/DLA claims. Hence, it would appear that while the effects of health, based on the Banks et al. (2015) measure, are more important in terms of economic magnitude than local labour effects for the likelihood of claiming ESA, local labour market conditions are still a relevant contributory factor. If we look at the results for ESA/IB together, they are very similar to those of ESA alone, albeit with lower levels of significance in most cases and smaller effect sizes. This is generally true for all the tables that follow, so for brevity we focus on the ESA results.

There is a clear evidence of persistence in the probability of benefit receipt, with those making an ESA claim in the previous year being 4.1 percentage points more likely to make a claim in the current year. Interestingly, the level of persistence in PIP or DLA upon the probability of claiming this type of benefit is comparable to that of ESA, and the health effects are marginally larger. The finding of persistence in benefit claims over time is consistent with the analysis of Berthoud (2004) and Emmerson et al. (2017). For each type of benefit unobserved heterogeneity is also apparent given the statistical significance and magnitude of the ρ parameter. This shows that the proportion of the total variance contributed by the panel level variance component is non-negligible and hence it is important to take the longitudinal structure of the data into account.

In terms of the control variables the results are largely as expected, although few of the controls have any significant effect on ESA claims. The exceptions are that having attained higher education other than degree level, i.e. possessing a teaching or nursing qualification, decreases the likelihood of claiming ESA (relative to having no education), whilst a 10% increase in household monthly equivalized income is associated with a 0.3 (1.1) percentage point higher probability of claiming ESA (PIP/DLA). In contrast being male and aged 25-34 or 45-54 reduces the likelihood of being on PIP/DLA; while having a degree, having children aged 12-15, being married and living in an urban area increases the likelihood of receiving this type of benefit. The year effects show that relative to the base period (prior to 2012) the probability of claiming ESA was increasing, conversely year effects are generally insignificant for PIP/DLA claims and are smaller in terms of magnitude compared to their associated impact on the likelihood of being in receipt of ESA benefits.

Table 5 reports the results from an equivalent model where health is measured via specific ADL problems; in Panel A these problems are included as a set of twelve dichotomous variables, whereas in Panel B the number of problems is used. The control variables are omitted from Table 5 for conciseness. As in Table 4 the local unemployment rate and benefit re-assessment rate have a significant effect on the propensity to claim ESA but not PIP/DLA, and state dependence is evident for each benefit type. In terms of the specific ADL, problems with mobility, lifting, memory/concentration, physical coordination and personal care all increase the propensity to claim ESA. Those individuals who report problems with lifting, manual dexterity and personal care also have a higher probability of claiming PIP/DLA. Focusing upon ESA, the largest health effect stems from lifting where having this specific health problem increases the probability of claiming ESA by 0.7 percentage points. Turning to the extent of health problems in Table 5 Panel B, the propensity to claim ESA or PIP/DLA increases with the number of health problems by about 0.5-0.6 percentage points for each additional health problem. Again, as found previously, this outweighs the effects stemming from local labour market conditions where in order to attain a similar magnitude to that found from the number of health problems the unemployment rate and benefit re-assessment rate would need to double.

Table 6 is an equivalent model to Table 5 but measuring health via the number of specific health conditions a respondent reports. The number of conditions is not statistically significant for ESA or ESA/IB claims, probably because most are chronic conditions and hence display little change over time in our model.[25] Although, interestingly the number of conditions does have a small negative effect on the likelihood of claiming PIP/DLA. For ESA claims all three local labour market variables are significant, suggesting that higher a local unemployment rate and replacement ratio increase the propensity to claim ESA, while high re-assessment rates lower the likelihood of receiving ESA. As expected these labour market variables are not significant for the propensity to claim PIP/DLA.

Table 7 again reports results from a similar model where health is measured via the SF-12 physical and mental health summary scores. Higher functioning on the physical health scale reduces the propensity to claim ESA, but size of the effect is very small, clearly dominated in terms of magnitude by local labour market conditions, where again all three are significant, with the largest marginal effect stemming from the replacement ratio. While better physical health reduces the propensity to claim PIP/DLA, better mental health increases this propensity. This implies that people with poor mental health are more likely to end up in out-of-work benefits relative to people with poor physical health (who can more readily access in-work benefits such as PIP/DLA). Again local labour market conditions do not effect PIP/DLA claims.

The results reported so far have shown that while health (measured in a number of alternative ways) is clearly an important determinant of the propensity to claim both ESA and PIP/DLA, local labour market characteristics are only relevant for ESA claims and not for PIP/DLA. This result is as expected given that PIP/DLA claims do not depend on labour market status, whereas eligibility for ESA is conditional on not being able to work. These findings are apparent after incorporating a lagged dependent variable, where there is clear evidence of state dependence in each type of benefit claim,

[25] This is why we do not report specifications which decompose the number of health conditions into specific types.

and the mean of time varying covariates (including health) in a correlated random effects framework which approximates a fixed effects estimator.[26]

Endogeneity

So far we have treated health as exogenous and labour market conditions as pre-determined (by entering them as a lag in the estimated models); we now investigate whether the results hold by treating these covariates as endogenous. For instance, the likelihood of making a benefit claim, local labour conditions and an individuals' health are all potentially jointly determined. In order to consider this potential endogeneity we estimate a linear probability model by GMM focusing upon the number of ADL health problems reported (as this is a continuous variable).[27] We employ a system GMM approach (Arellano and Bover, 1995; and Blundell and Bond, 1998), where: the dependent variable appears with one lag and at most two lags are used as instruments; all local labour market covariates are treated as endogenous and appear with one lag using an additional lag as an instrument; the number of health problems is also considered endogenous and is entered contemporaneously with an additional lag used as an instrument. The results are shown in Table 8 where for ESA and PIP/DLA the Sargan test that the over-identifying restrictions are valid cannot be rejected, and higher order lags of the error terms are serially uncorrelated as desired. The results show clear evidence of dynamics, consistent with our previous findings, with state dependence in each benefit state. Even after treating health as an endogenous variable we still find that the number of health problems increase the likelihood of claiming each benefit type (as found in Table 5 Panel B). Moreover, local labour market effects still remain and as expected only influence ESA claims, although there is now evidence that the benefit replacement ratio increases the likelihood of ESA benefit claims. Interestingly, consistent with the previous analysis the results reveal that health effects dominate local labour market effects in terms of economic magnitude.

[26] Alternative specifications have also been estimated where the local labour market covariates, U_{krt-1}, were entered one at a time rather than simultaneously. The point estimates of ψ_k were found to be virtually identical in terms of magnitude and statistical significance to those reported in Tables 4 to 7.
[27] Although the dependent variable whether the individual receives benefits, b_{it}, is binary GMM does not impose any distributional assumptions on the errors and so can be applied to this framework.

Heterogeneity

Having explored endogeneity issues and found that the results are similar to the correlated random effects approach in terms of statistical significance and direction of influence of both health and local labour market effects, we now return to the correlated random effects framework of equations 1A and 1B in order to explore whether there is heterogeneity in the reported local labour market and health effects by considering interactions. Given no local labour market effects were found for the probability of claiming PIP/DLA, for brevity the focus is now solely upon the likelihood of claiming ESA. We interact the effects of health (based on the number of ADL problems measure initially reported in Table 5 Panel B) and the three local labour market variables with: (i) gender i.e. male or female; (ii) education level i.e. A level or above or below A level; (iii) income i.e. above or at the poverty line or below the poverty line (in the first wave the individual was observed);[28] and (iv) urban or rural location of residence.[29] We also consider: (v) regional differentials (based upon government statistical region indicators); and (vi) life-cycle effects (defined by a series of age indicators, as described in Section 4). In terms of equation 1A for gender (model 1), education (model 2), poverty (model 3) and location of residence (model 4) $G = 2$; whilst for regional differentials (model 5) $G = 11$ and life-cycle effects based upon five age bands (model 6) $G = 5$. Whilst interpreting interaction effects is straightforward in linear models, in a non-linear framework the coefficient on the interaction term does not provide the change in the partial effect of either variable on the conditional mean function. Hence, interpreting the first derivative of the multiplicative term is insufficient as the cross partial derivative between the two variables needs to be taken into account, see Ai and Norton (2003) and Greene (2010). Typically this is different from the first derivative of $E(b_{it})$ with respect to the multiplicative terms, $\{H_{jit} \times S_{git}\}$ and $\{U_{krt-1} \times S_{git}\}$, in equation 1A; furthermore, the statistical significance of the interaction term cannot be assessed with a simple t-test. Consequently, in what

[28] Poverty is defined as having equivalized income less than 60% of the median household. This is consistent with the measure of poverty used in official UK statistics www.gov.uk/government/statistics/households-below-average-income-199495-to-201718.

[29] Urban areas are defined as settlements with a population of 10,000 or more according to Department for Environment, Food and Rural Affairs (DEFRA) www.gov.uk/government/collections/rural-urban-classification.

follows to resolve this issue we examine the interaction effects of two variables graphically, by plotting how the partial effect of one variable (e.g. health) changes with that variable for different values of the second variable (e.g. gender) and providing corresponding confidence intervals.

Figure 6 shows the results for gender (model 1), education (model 2), poverty (model 3) and location of residence (model 4). Each sub-plot has a reference line on the vertical axis at zero as we are looking for effects that are different to zero. We provide average marginal effects (AMEs) for each group, e.g. model 1 males and females, along with 95 percent confidence intervals. Looking first at gender, in the first pane of Figure 6, the effect of health problems has a similar effect across the sexes although the slope of the AMEs across the number of health problems, which indicates the effect upon the probability of claiming ESA, is marginally steeper for females. Higher levels of the unemployment rate have no significant impact upon the likelihood of benefit receipt for women, but unemployment does increase the propensity to claim ESA for men rising monotonically in the local unemployment rate. Conversely, the local benefit replacement ratio only influences women's propensity to claim ESA, although the level of significance dissipates as the replacement rate increases, whilst the benefit re-assessment rate has similar effects for both sexes reducing the likelihood of ESA claims.

We now focus upon whether there are differential effects upon the probability of claiming ESA between people with higher levels of qualifications (A level and above) compared to those with a lower level of education (below A level), shown in the second pane of Figure 6. As the number of health problems escalate, three or more, those individuals who are more highly qualified have a greater propensity to claim benefits compared to those with lower educational attainment (culminating in a 2 percentage point differential). The local unemployment rate and the benefit replacement ratio only have a statistically significant and positive effect on the likelihood of claiming ESA for the lower educated group. Considering the replacement ratio the differential in the average marginal effect between the two educational groups is approximately 1 percentage point higher for the less educated group. Interestingly, the effect of benefit re-assessment rate on the propensity to claim ESA is the same irrespective of educational attainment.

The third pane of Figure 6 considers whether heterogeneity exists between those households which are at or above the poverty line in comparison to those below the poverty line. Interestingly, the influence of health upon the propensity to claim ESA is more apparent in terms of the magnitude of the AMEs for those households where equivalized income is equal to or higher than 60% of the median, for those in the worst health state the differential is 2.4 percentage points. The unemployment rate has a larger positive effect on benefit receipt for those below the poverty line, whilst conversely the benefit re-assessment rate decreases the probability of claiming ESA to a greater extent for those households below the poverty line.

In the final pane of Figure 6 we consider whether there are differences in local labour markets effects and health upon the likelihood of benefit receipt between urban and rural areas, which a priori one may expect given that labour market opportunities are likely to be worse in rural areas. The effect of worsening health upon the probability of claiming ESA is positive in both urban and rural areas, but the slope of the AMEs is noticeably more acute in rural areas. The local unemployment rate (benefit re-assessment rate) increase (decrease) the propensity to claim ESA but in urban areas only. Next, as an alternative way to explore whether there are differential effects by location of residence we consider where an individual lives in more detail by looking at eleven different UK regions.

The geographic regions we focus on are: North East; North West; Yorkshire and the Humber; East Midlands; West Midlands; East of England; London; South East; South West; Wales and Scotland. We report AMEs for each region separately along with 95 percent confidence intervals. The upper left hand pane of Figure 7 considers how an increasing number of health problems impacts on ESA claims by region. Clearly, across all regions the effects are statistically significant from zero irrespective of the number of problems, increasing the probability of claiming ESA, although confidence intervals become wider as the number of problems approaches six of more. Moreover, the effects are found to be more acute in the East of England and Wales, given the steeper slopes. For example, those individuals who report six or more ADL health problems and reside in Wales (East of England) have around a 7 (8) percentage point higher probability of claiming ESA. The upper right hand pane shows how higher local unemployment rates affect the probability of making ESA claims. In the East of England and Scotland a higher unemployment rate is associated with an increase in the likelihood of claiming ESA, whilst the effects are negligible for other regions. In the lower left pane of Figure 7 the focus is upon the benefit replacement ratio and the potential differing impacts on ESA claims by region, where the only significant effects are for the West Midlands culminating in a 15 percentage point increase in the likelihood of ESA benefit receipt when the replacement ratio is at its most extreme. Turning to the benefit re-assessment rate the lower right pane of Figure 7 reveals generally small effects across all regions, where typically significance is only evident at low re-assessment rates being inversely related with the probability of claiming ESA with the effects dissipating at higher rates with the most noticeable effects apparent for the North East.

In Figure 8 we explore whether the effect of health problems and local labour conditions impact differently upon the propensity to claim ESA by an individuals' age (model 6). Specifically, we consider five age groups i.e. 16-24, 25-34, 35-44, 45-54 and 55-65. The upper left hand pane considers how an increasing number of health problems impacts on ESA claims by age group. For each age band health problems increase the probability of claiming ESA, this is most (least) apparent for those aged 16-24 (55-65) where someone with six or more health problems is over 11 (5) percentage points more likely to receive benefits. The upper right hand pane of Figure 8 shows how higher local unemployment rates affect the probability of making ESA claims by age group. Clearly, there are differential effects of increasing unemployment rates on benefit claims by age, especially for 25-34 and 55-65 year olds – being most stark for the latter group, increasing the likelihood of ESA benefits by around 1 percentage points for those living in locations with the most severe levels of unemployment. In the lower left pane of Figure 8 the focus is upon the benefit replacement ratio and the potential differing impact on ESA claims by age, where the only statistically significant effects stem from those aged 25-34 where a higher replacement ratio increases the probability of claiming ESA. The lower right pane considers how a higher benefit re-assessment rate impacts on ESA claims, where it is apparent that largest effects occur for older individuals, especially those aged 45-54, where a higher re-assessment rate dampens the negative effect upon ESA claims.

6. CONCLUSION

This paper uses individual longitudinal data from 2009 to 2018 in a dynamic panel framework to explore the relative importance of health status, benefit generosity and local labour market conditions for disability benefit claims in the modern UK labour market. Our focus is particularly on spatial variation in claims, and we find that, in line with older evidence, while health status is clearly important, geographic variation in labour market conditions and benefit generosity still influence the propensity to claim ESA, a disability benefit that is conditional on not working. For example, a doubling of the local unemployment rate increases the probability of making an ESA claim by approximately 0.5 percentage points. In contrast these local factors do not influence PIP/DLA claims, which is as expected since these benefits are provided to meet the additional costs of disability and are not dependent on labour market status. We also find that the speed at which new WCA are being introduced locally to re-assess claims is a factor in reducing the propensity to claim ESA. This may suggest that WCA is doing the job it was introduced to do, and reducing the number of claims overall.

These average effects also mask important heterogeneity by sex, age, education level, income and geography. For example, male ESA claims are more positively affected by the local unemployment rate relative to females, whilst conversely the benefit replacement ratio only influences the probability of benefit receipt for females. Those individuals with qualifications below that of A level are affected by higher local unemployment rates and a higher benefit replacement ratio, increasing the probability of benefit receipt relative to those with A level education or above (for this more educated group the aforementioned local labour market conditions have no effect). Those below the poverty line are affected to a greater extent (relative to those households at or above 60% of median income) by higher unemployment rates and a higher benefit re-assessment rate. Individuals in the 55-65 age group are most affected by higher unemployment rates monotonically increasing the probability of claiming ESA. Those individuals aged 16-24 are more likely to claim ESA increasing monotonically in the number health of problems. The benefit re-assessment rate has larger effects upon benefit claims for those aged 45 and above, decreasing the probability of ESA but at a diminishing rate. In terms of geographical location of residence, unemployment has a larger impact on ESA claims in the East of England and Scotland, but there is little evidence of any differential effects from local labour market factors in other areas. An increasing number of health problems has similar effects across each regions albeit being more extreme in the East of England and Wales. In summary, it would appear that there are certain groups who are more sensitive to local labour market conditions, in particular the: less educated; poorest households; those living in urban areas (although this obscures some regional variation) and older individuals (i.e. considering unemployment).

These results have important implications for policy. The tools required to reduce the disability benefits burden are very different in response to the demand and supply side influences. Older government policy initiatives aimed at reducing the disability benefit roll seemed to assume that this was a labour supply issue. However, more recently government seems to have acknowledged the complexity of the challenge. They have established the cross-department Work and Health Unit to deliver change and their 2017 White Paper recognises the complementary roles of the welfare and employment system, healthcare services and employers. Further, the deep and persistent geographic inequalities that our results reflect might require very specific spatially informed policies since whole communities may be at risk from social exclusion where disability benefit rolls are particularly concentrated. While, Anyadike-Danes (2010) described the government's welfare reform agenda for disability as 'aspatial', there is some indication that this is changing. The 2016 Green paper and the 2017 White Paper call for a 'place-based approach', emphasising the need to work in partnership with local organisations and devolved administrations to ensure that local needs are met. Our results are timely and suggest that this spatially informed policy is essential.

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TABLE 1: Transition matrix of benefit status

		ESA	IB	PIP|DLA	NO BENEFITS
		t			
$t-1$	ESA	71.98%	2.34%	8.23%	17.46%
	IB	18.71%	49.61%	13.88%	17.80%
	PIP|DLA	11.66%	6.01%	62.40%	19.93%
	NO BENEFITS	0.89%	0.24%	0.82%	98.06%
		3.52%	**1.32%**	**3.00%**	**92.17%**

Note: ESA = Employment Support Allowance, IB = Incapacity Benefit; PIP|DLA = Personal Independence Payments and/or Disability Living Allowance; NO BENEFITS = not receiving ESA, IB, PIP or DLA.

TABLE 2: Summary statistics – individual, household and local authority district controls

	MEAN	STD. DEV	MIN	MAX
Individual and household, $\boldsymbol{X}_{it}$				
Male	0.476	0.499	0	1
White	0.810	0.392	0	1
Immigrant	0.002	0.046	0	1
Aged 16-24	0.050	0.218	0	1
Aged 25-34	0.162	0.368	0	1
Aged 35-44	0.259	0.438	0	1
Aged 45-54	0.317	0.465	0	1
No. Adults	2.415	1.070	1	12
No. Kids 0-2	0.090	0.310	0	5
No. Kids 3-4	0.078	0.280	0	3
No. Kids 5-11	0.316	0.634	0	5
No. Kids 12-15	0.194	0.464	0	5
Degree	0.264	0.441	0	1
Other High	0.104	0.305	0	1
A level	0.079	0.269	0	1
AS level	0.009	0.095	0	1
GCSE	0.203	0.402	0	1
Other qual.	0.073	0.259	0	1
Married	0.535	0.499	0	1
Home owned outright	0.199	0.399	0	1
Mortgage with equity	0.494	0.500	0	1
Mortgage negative equity	0.035	0.184	0	1
Log equivalized income	7.585	0.684	0	10.249
Urban area	0.810	0.393	0	1
North East	0.036	0.186	0	1
North West	0.112	0.316	0	1
Yorkshire	0.093	0.291	0	1
East Midlands	0.079	0.269	0	1
West Midlands	0.092	0.289	0	1
East of England	0.082	0.275	0	1
South East	0.116	0.320	0	1
South West	0.081	0.273	0	1
Wales	0.075	0.264	0	1
Scotland	0.091	0.288	0	1
Local authority district, U_{rt}				
Unemployment rate, UE (%)	6.916	2.928	1.200	18.901
Replacement ratio, RR (%)	16.018	2.621	6.015	24.282
Re-assessment rate, RAR (%)	4.880	2.188	0.630	12.986
Number of Individuals (N)		26,939		
Observations (NT)		95,247		

TABLE 3: Summary statistics – health controls

	MEAN	STD. DEV	MIN	MAX
Banks et al. (2015), H_{jit} $(J = 3)$				
Health mild	0.059	0.235	0	1
Health moderate	0.022	0.148	0	1
Health severe	0.016	0.127	0	1
Health problems, H_{jit} $(J = 11)$				
Mobility	0.089	0.285	0	1
Lifting, carrying or moving objects	0.096	0.295	0	1
Manual dexterity	0.039	0.195	0	1
Continence	0.025	0.156	0	1
Hearing	0.017	0.127	0	1
Sight	0.018	0.131	0	1
Communication or speech	0.012	0.109	0	1
Memory or ability to concentrate	0.042	0.202	0	1
Recognising physical danger	0.008	0.087	0	1
Physical coordination	0.035	0.184	0	1
Personal care	0.028	0.166	0	1
Other type of problem	0.009	0.095	0	1
Health problems, H_{jit} $(J = 1)$				
Number of health problems, H_{it}	0.401	1.129	0	6
Health conditions, H_{jit} $(J = 1)$				
Number of health conditions[#], H_{it}	0.202	0.166	0	6
Short Form 12 generic health instrument, H_{jit} $(J = 2)$				
SF12 physical health index	45.790	18.294	0	74.17
SF12 mental health index	43.309	17.527	0	76.12
Number of Individuals (N)		26,939		
Observations (NT)		95,247		

Notes: [#]the number of health conditions comprises a count of the whether the individual has any of the following: asthma (0.050); arthritis (0.027); diabetes (0.012); blood pressure (0.044); depression (0.025); and any other health condition (0.017), with the mean given in parenthesis.

TABLE 4: Dynamic probability models – health based upon Banks et al. (2015)

	ESA		ESA|IB		PIP|DLA	
Male	-0.0008	*(0.71)*	-0.0002	*(0.17)*	-0.0048	*(4.72)*
White	0.0002	*(0.13)*	-0.0001	*(0.62)*	0.0024	*(1.56)*
Immigrant	0.0079	*(1.03)*	0.0116	*(1.64)*	-0.0070	*(0.62)*
Aged 16-24	-0.0019	*(0.30)*	-0.0044	*(0.63)*	-0.0064	*(0.85)*
Aged 25-34	-0.0015	*(0.29)*	-0.0046	*(0.86)*	-0.0105	*(2.05)*
Aged 35-44	-0.0005	*(0.14)*	-0.0004	*(0.11)*	-0.0050	*(1.39)*
Aged 45-54	-0.0008	*(0.36)*	0.0017	*(0.68)*	-0.0056	*(2.41)*
No. Adults	-0.0016	*(1.51)*	-0.0012	*(1.08)*	-0.0016	*(1.41)*
No. Kids 0-2	0.0026	*(1.00)*	0.0015	*(0.55)*	0.0010	*(0.40)*
No. Kids 3-4	0.0044	*(1.57)*	0.0041	*(1.39)*	0.0041	*(1.66)*
No. Kids 5-11	-0.0021	*(0.96)*	-0.0011	*(0.46)*	0.0025	*(1.31)*
No. Kids 12-15	-0.0003	*(0.16)*	-0.0012	*(0.57)*	0.0051	*(2.94)*
Degree	-0.0103	*(1.85)*	-0.0038	*(0.26)*	0.0206	*(1.91)*
Other High	-0.0227	*(2.26)*	-0.0159	*(1.50)*	0.0091	*(1.04)*
A level	-0.0177	*(1.37)*	-0.0185	*(1.12)*	0.0200	*(1.13)*
AS level	-0.0115	*(1.15)*	-0.0011	*(0.09)*	0.0065	*(0.93)*
GCSE	-0.0244	*(1.88)*	-0.0108	*(0.70)*	0.0086	*(0.73)*
Other qual.	0.0078	*(0.76)*	0.0080	*(0.64)*	0.0103	*(0.68)*
Married	-0.0043	*(1.55)*	-0.0058	*(2.02)*	0.0139	*(4.91)*
Home owned outright	0.0064	*(1.46)*	0.0081	*(1.69)*	0.0008	*(0.18)*
Mortgage with equity	-0.0020	*(0.50)*	-0.0009	*(0.21)*	-0.0001	*(0.02)*
Mortgage negative equity	0.0020	*(0.36)*	0.0048	*(0.88)*	0.0041	*(0.86)*
Log equivalized income	0.0025	*(3.66)*	0.0056	*(6.16)*	0.0105	*(7.41)*
Urban area	0.0005	*(0.35)*	0.0029	*(1.74)*	0.0038	*(2.60)*
2012	0.0091	*(4.70)*	0.0043	*(2.19)*	0.0013	*(0.61)*
2013	0.0141	*(6.22)*	0.0025	*(1.17)*	-0.0011	*(0.53)*
2014	0.0231	*(8.10)*	0.0105	*(3.84)*	0.0040	*(1.51)*
2015	0.0287	*(8.56)*	0.0155	*(4.65)*	0.0069	*(2.12)*
2016	0.0310	*(8.40)*	0.0158	*(4.21)*	0.0060	*(1.66)*
2017	0.0305	*(8.01)*	0.0159	*(3.97)*	0.0089	*(2.26)*
2018	0.0285	*(7.34)*	0.0140	*(3.35)*	0.0071	*(1.71)*

TABLE 4 (cont.): Dynamic probability models – health based upon Banks et al. (2015)

	ESA		ESA|IB		PIP|DLA	
ESA_{t-1}	0.0410	*(20.21)*				
$ESA\|IB_{t-1}$			0.0438	*(22.40)*		
$PIP\|DLA_{t-1}$					0.0495	*(22.28)*
Log UE_{t-1}	0.0047	*(2.63)*	0.0033	*(1.76)*	0.0001	*(0.60)*
Log RR_{t-1}	0.0073	*(1.40)*	0.0063	*(1.18)*	0.0020	*(0.38)*
Log RAR_{t-1}	-0.0082	*(3.46)*	-0.0073	*(2.81)*	0.0011	*(0.43)*
Mild	0.0159	*(9.21)*	0.0152	*(8.43)*	0.0134	*(7.92)*
Moderate	0.0181	*(7.73)*	0.0202	*(8.14)*	0.0243	*(9.99)*
Severe	0.0248	*(8.73)*	0.0254	*(8.01)*	0.0299	*(9.27)*
ρ; p-value	0.4073*; p=0.000*		0.3669*; p=0.000*		0.3240*; p=0.000*	
N			95,247			
NT			26,939			

Notes: (i) other controls include region dummies, the mean of time varying covariates, and the initial observed benefit state; (ii) average marginal effects are reported along with heteroscedastic robust t-statistics in parenthesis.

TABLE 5: Dynamic probability models – health problems

PANEL A: TYPE OF PROBLEM	ESA		ESA|IB		PIP|DLA	
ESA_{t-1}	0.0394	*(19.88)*				
$ESA\|IB_{t-1}$			0.0430	*(22.46)*		
$PIP\|DLA_{t-1}$					0.0487	*(21.83)*
Log UE_{t-1}	0.0046	*(2.63)*	0.0036	*(1.88)*	0.0002	*(0.01)*
Log RR_{t-1}	0.0047	*(0.93)*	0.0045	*(0.84)*	0.0022	*(0.44)*
Log RAR_{t-1}	-0.0075	*(3.23)*	-0.0067	*(2.62)*	0.0007	*(0.31)*
Mobility	0.0065	*(3.46)*	0.0079	*(3.96)*	0.0099	*(5.41)*
Lifting, carrying, moving objects	0.0074	*(4.19)*	0.0065	*(3.33)*	0.0091	*(5.01)*
Manual dexterity	0.0019	*(1.06)*	0.0030	*(1.41)*	0.0046	*(2.14)*
Continence	-0.0016	*(0.69)*	0.0020	*(0.82)*	0.0051	*(1.97)*
Hearing	-0.0041	*(1.28)*	-0.0039	*(1.09)*	-0.0009	*(0.28)*
Sight	0.0036	*(1.33)*	0.0024	*(0.82)*	0.0041	*(1.35)*
Communication or speech	0.0002	*(0.06)*	0.0020	*(0.66)*	0.0043	*(1.23)*
Memory/ability to concentrate	0.0067	*(3.76)*	0.0063	*(3.26)*	0.0035	*(1.63)*
Recognising physical danger	0.0003	*(0.10)*	0.0002	*(0.06)*	-0.0016	*(0.39)*
Physical coordination	0.0059	*(3.04)*	0.0054	*(2.40)*	0.0038	*(1.60)*
Personal care	0.0053	*(2.58)*	0.0026	*(1.09)*	0.0056	*(2.26)*
Other type of health problem	0.0006	*(0.21)*	0.0063	*(1.93)*	0.0045	*(1.24)*
N (NT)			26,939 (95,247)			

PANEL B: NO. OF PROBLEMS	ESA		ESA|IB		PIP|DLA	
ESA_{t-1}	0.0406	*(20.15)*				
IB_{t-1}						
$ESA\|IB_{t-1}$			0.0438	*(22.48)*		
$PIP\|DLA_{t-1}$					0.0488	*(21.97)*
Log UE_{t-1}	0.0048	*(2.66)*	0.0036	*(1.89)*	0.0003	*(0.17)*
Log RR_{t-1}	0.0068	*(1.33)*	0.0062	*(1.18)*	0.0026	*(0.53)*
Log RAR_{t-1}	-0.0084	*(3.57)*	-0.0076	*(2.95)*	0.0004	*(0.18)*
Number of health problems	0.0051	*(10.62)*	0.0054	*(10.56)*	0.0062	*(12.55)*
N (NT)			26,939 (95,247)			

Notes: (i) other controls as in Table 4; (ii) average marginal effects are reported along with heteroscedastic robust t-statistics in parenthesis.

TABLE 6: Dynamic probability models – health conditions

	ESA		ESA|IB		PIP|DLA	
ESA_{t-1}	0.0510	*(18.93)*				
$ESA\|IB_{t-1}$			0.0546	*(22.48)*		
$PIP\|DLA_{t-1}$					0.0745	*(23.34)*
Log UE_{t-1}	0.0053	*(2.77)*	0.0036	*(1.80)*	0.0006	*(0.32)*
Log RR_{t-1}	0.0153	*(2.72)*	0.0134	*(2.35)*	0.0147	*(1.45)*
Log RAR_{t-1}	-0.0087	*(3.41)*	-0.0077	*(2.76)*	0.0002	*(0.09)*
Number of health conditions	-0.0002	*(0.18)*	-0.0002	*(0.15)*	-0.0020	*(1.91)*
N			26,939			
NT			95,247			

Notes: (i) other controls as in Table 4; (ii) average marginal effects are reported along with heteroscedastic robust t-statistics in parenthesis.

TABLE 7: Dynamic probability models – SF12 physical and mental health

	ESA		ESA|IB		PIP|DLA	
ESA_{t-1}	0.0504	*(20.35)*				
$ESA\|IB_{t-1}$			0.0558	*(23.61)*		
$PIP\|DLA_{t-1}$					0.0701	*(24.73)*
Log UE_{t-1}	0.0045	*(2.45)*	0.0035	*(1.53)*	-0.0004	*(0.20)*
Log RR_{t-1}	0.0127	*(2.32)*	0.0090	*(1.85)*	0.0099	*(1.53)*
Log RAR_{t-1}	-0.0085	*(3.46)*	-0.0049	*(2.60)*	0.0011	*(0.42)*
SF12 physical health	-0.0001	*(2.27)*	-0.0002	*(3.04)*	-0.0002	*(3.34)*
SF12 mental health	-0.0001	*(1.40)*	-0.0001	*(0.87)*	0.0002	*(4.09)*
N			26,939			
NT			95,247			

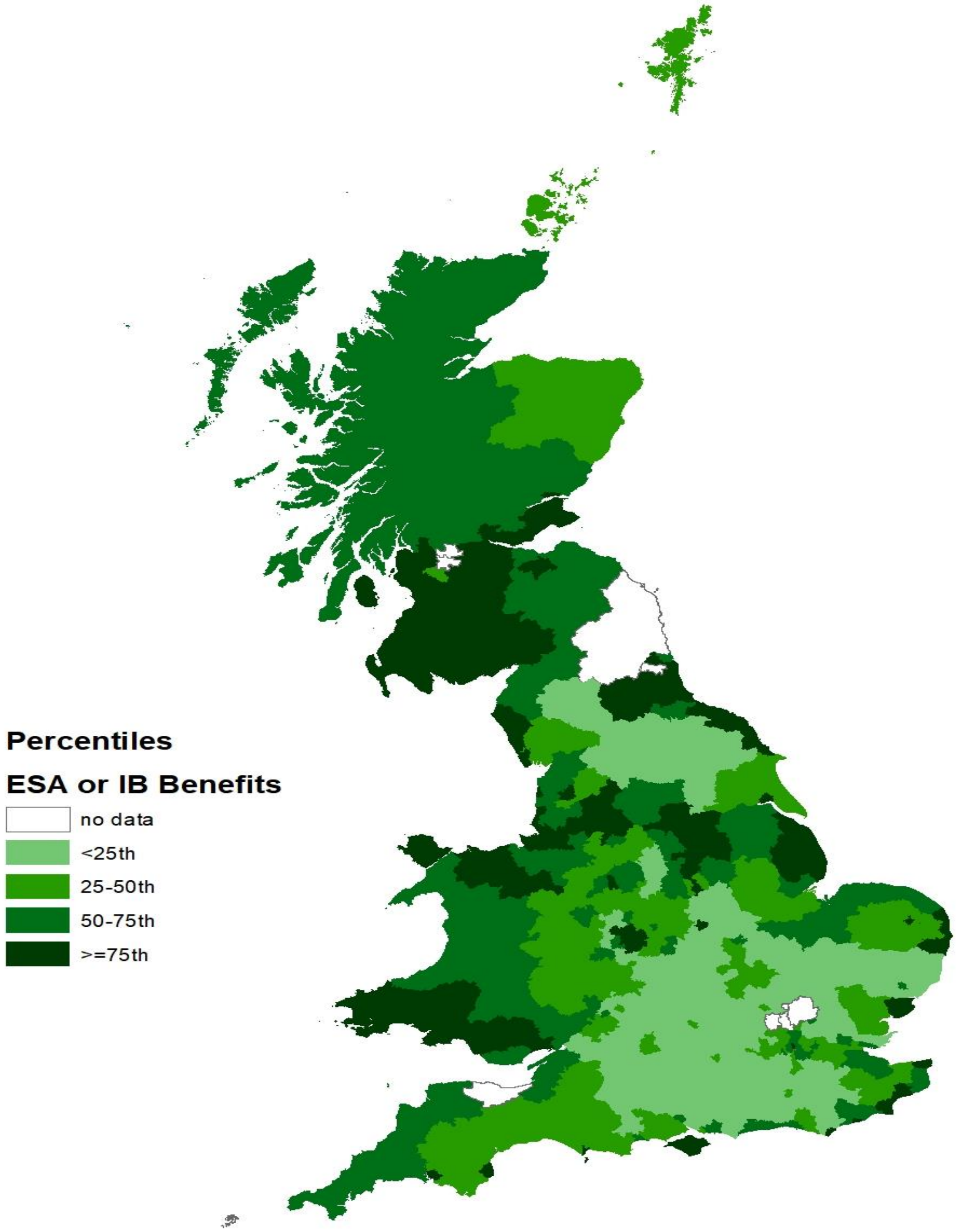
Notes: (i) other controls as in Table 4; (ii) average marginal effects are reported along with heteroscedastic robust t-statistics in parenthesis.

TABLE 8: GMM linear probability model – health problems

	ESA		ESA|IB		PIP|DLA	
ESA_{t-1}	0.3520	*(14.59)*				
$ESA\|IB_{t-1}$			0.2865	*(15.04)*		
$PIP\|DLA_{t-1}$					0.2714	*(10.81)*
Log UE_{t-1}	0.0465	*(4.39)*	0.0306	*(2.83)*	0.0071	*(0.62)*
Log RR_{t-1}	0.0106	*(3.36)*	0.0064	*(2.04)*	0.0252	*(0.76)*
Log RAR_{t-1}	-0.0266	*(2.96)*	-0.0152	*(1.81)*	0.0073	*(0.93)*
Number of health problems	0.0704	*(8.40)*	0.0508	*(5.51)*	0.0639	*(6.63)*
Wald $\chi^2(43)$; *p-value*	1438.17; *p=0.000*		609.67; *p=0.000*		776.45; *p=0.000*	
Test for AR(2) in errors; *p-value*	-0.2265; *p=0.821*		2.1337; *p=0.033*		0.0837; *p=0.933*	
Test for AR(3) in errors; *p-value*	-0.3577; *p=0.721*		-0.0814; *p=0.935*		-0.0471; *p=0.962*	
Sargan over-identification test $\chi^2(26)$; *p-value*	30.99; *p=0.228*		38.88; *p=0.059*		24.11; *p=0.569*	
Number of instruments			96			
N			26,939			
NT			95,247			

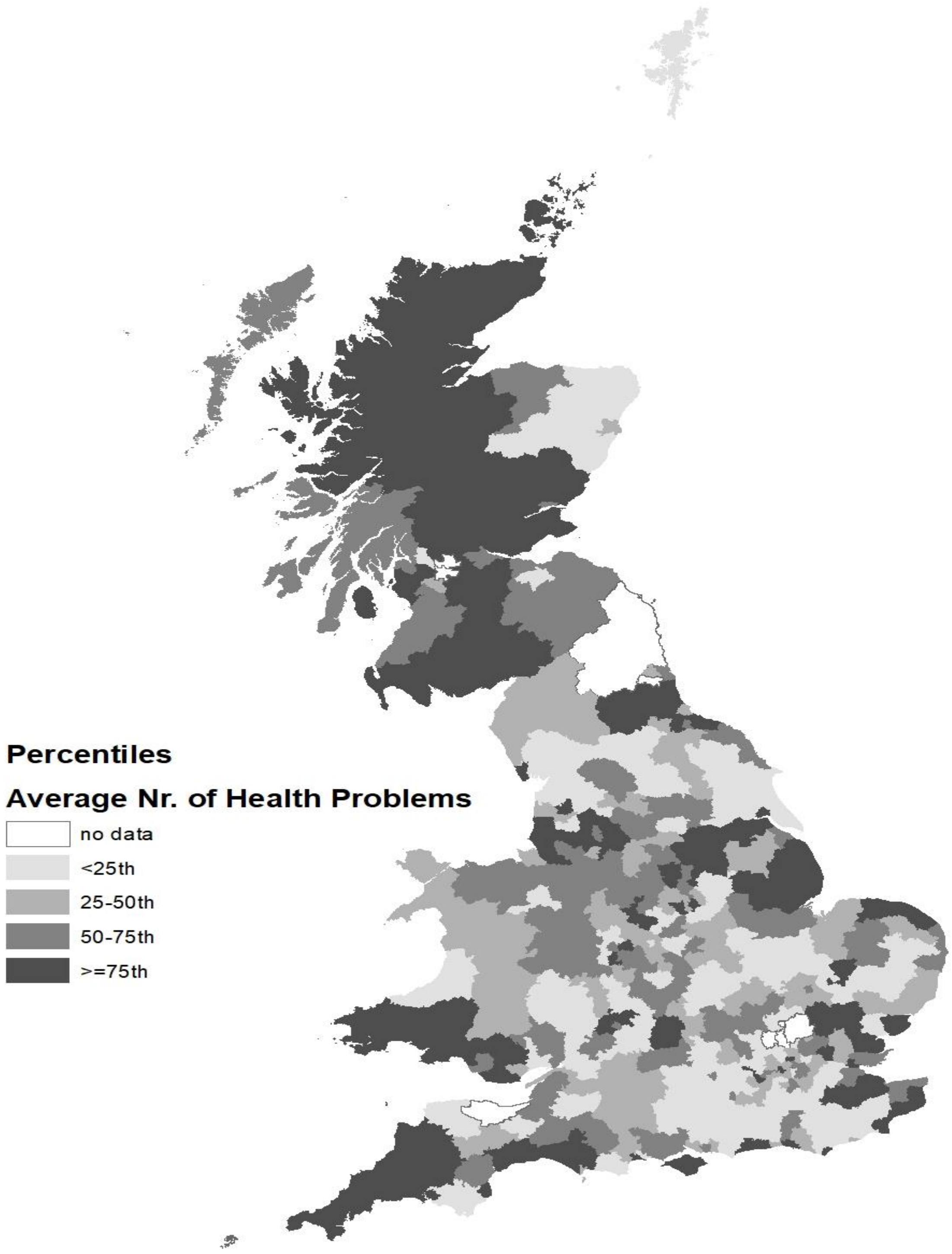
Notes: (i) other controls as in Table 4; (ii) the dependent variable appears with one lag and at most two lags are used as instruments; all local labour market covariates are treated as endogenous and appear with one lag using an additional lag as an instrument; the number of health problems is also considered endogenous and is entered contemporaneously with an additional lag used as an instrument; all other covariates act as first difference instruments in the differenced equation.

FIGURE 1: Claimant rates by quartile (produced in ArcGIS using NOMIS data)



Note: The claimant rate is the number of ESA or IB claimants as a percentage of the LAD population aged 16-65.

FIGURE 2: Average number of health problems by quartile (produced in ArcGIS using UKHLS data)



Note: Health problems are defined according to problems with Activities of Daily Living (ADL).

FIGURE 3: Unemployment rate by quartile (produced in ArcGIS using NOMIS data)

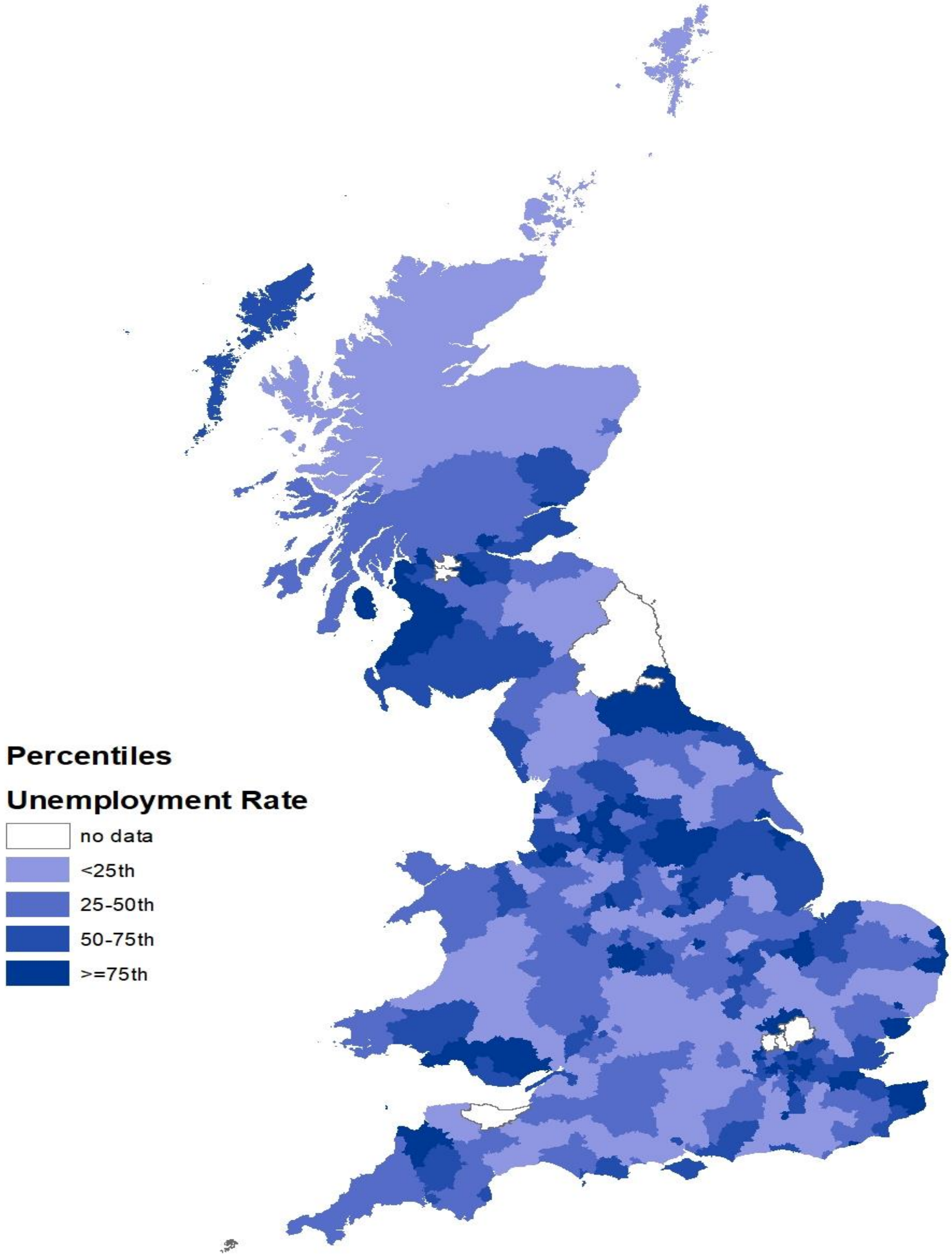
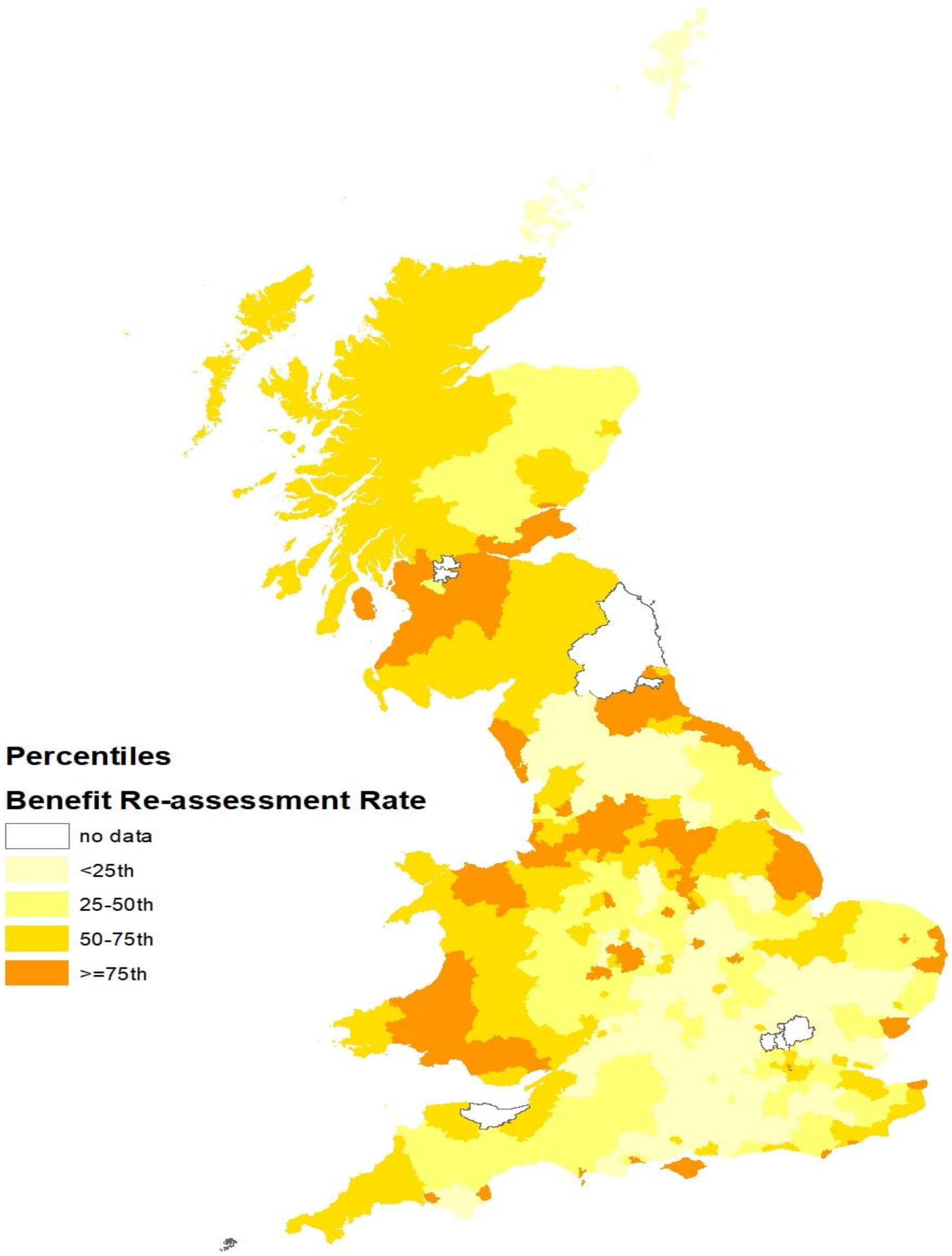
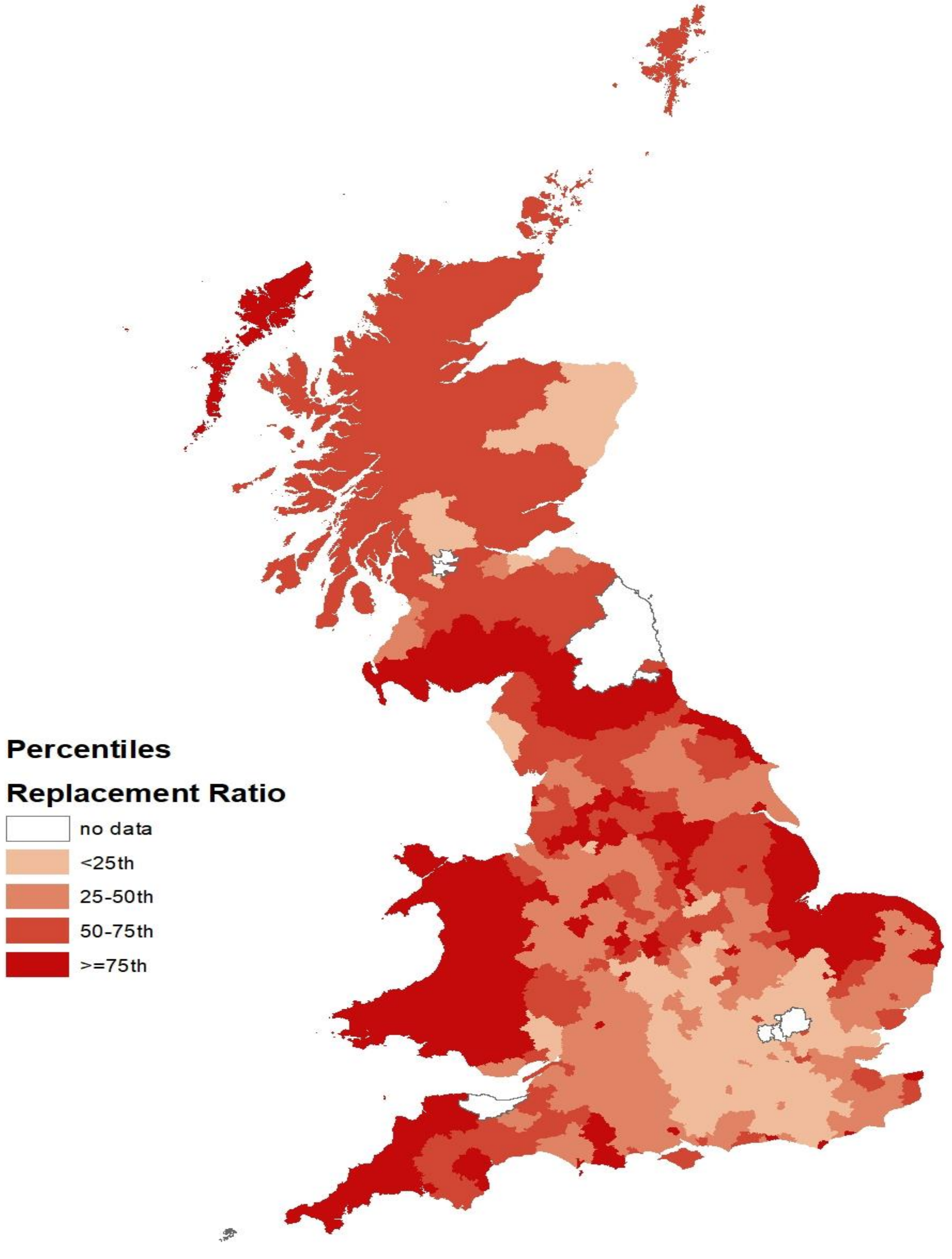


FIGURE 4: Benefit re-assessment rate by quartile (produced in ArcGIS using Stat-Xplore and NOMIS data)



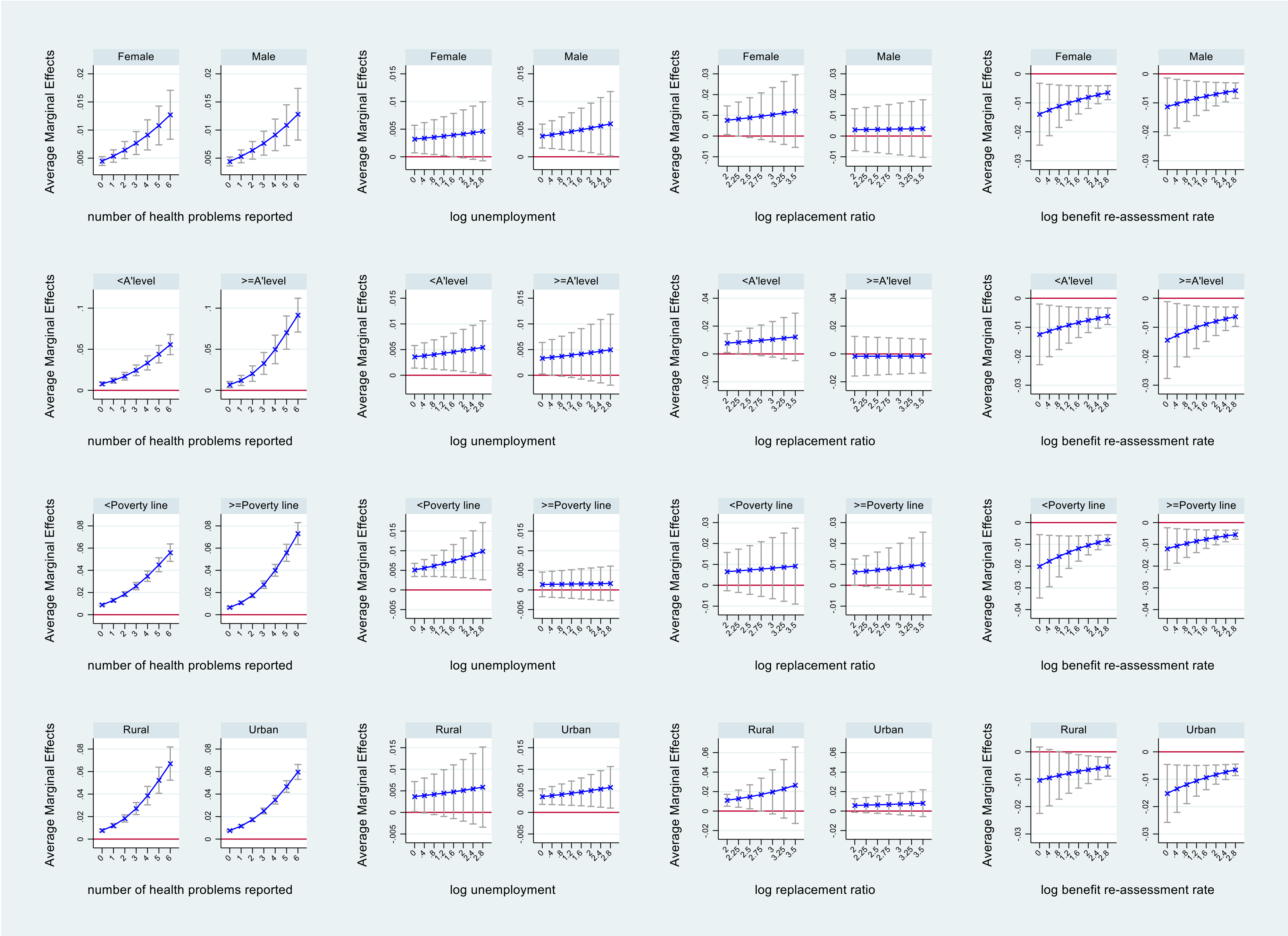
Note: The benefit re-assessment rate is total number of cases re-assessed by WCA as a percentage of the local working age population.

FIGURE 5: Benefit replacement rate by quartile (produced in ArcGIS using NOMIS data)



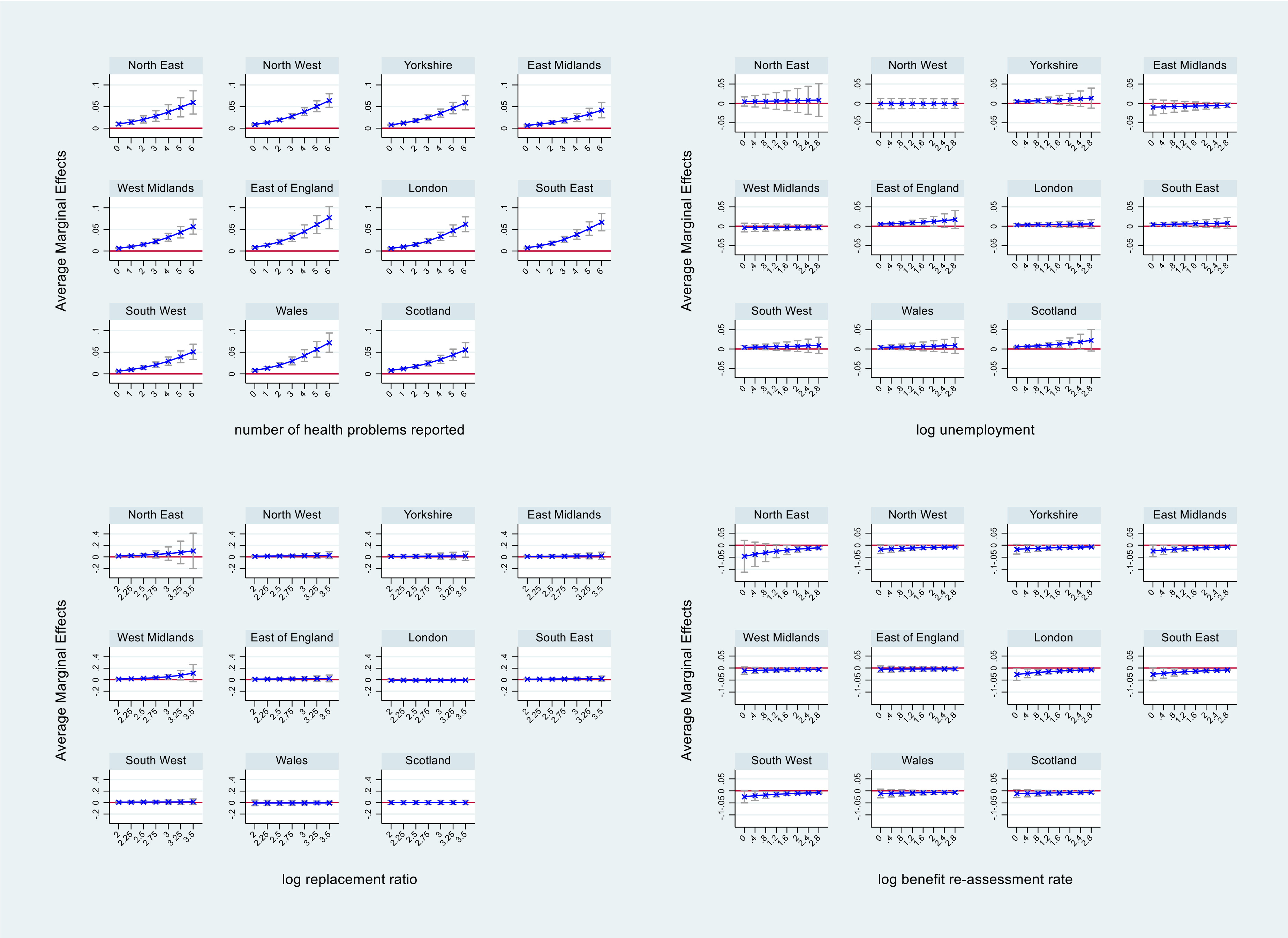
Note: The benefit replacement rate is the average level of disability benefits as a percentage of the local average median wage.

FIGURE 6: Heterogeneity – gender (model 1), qualifications (model 2), poverty (model 3) and location of residence (model 4)



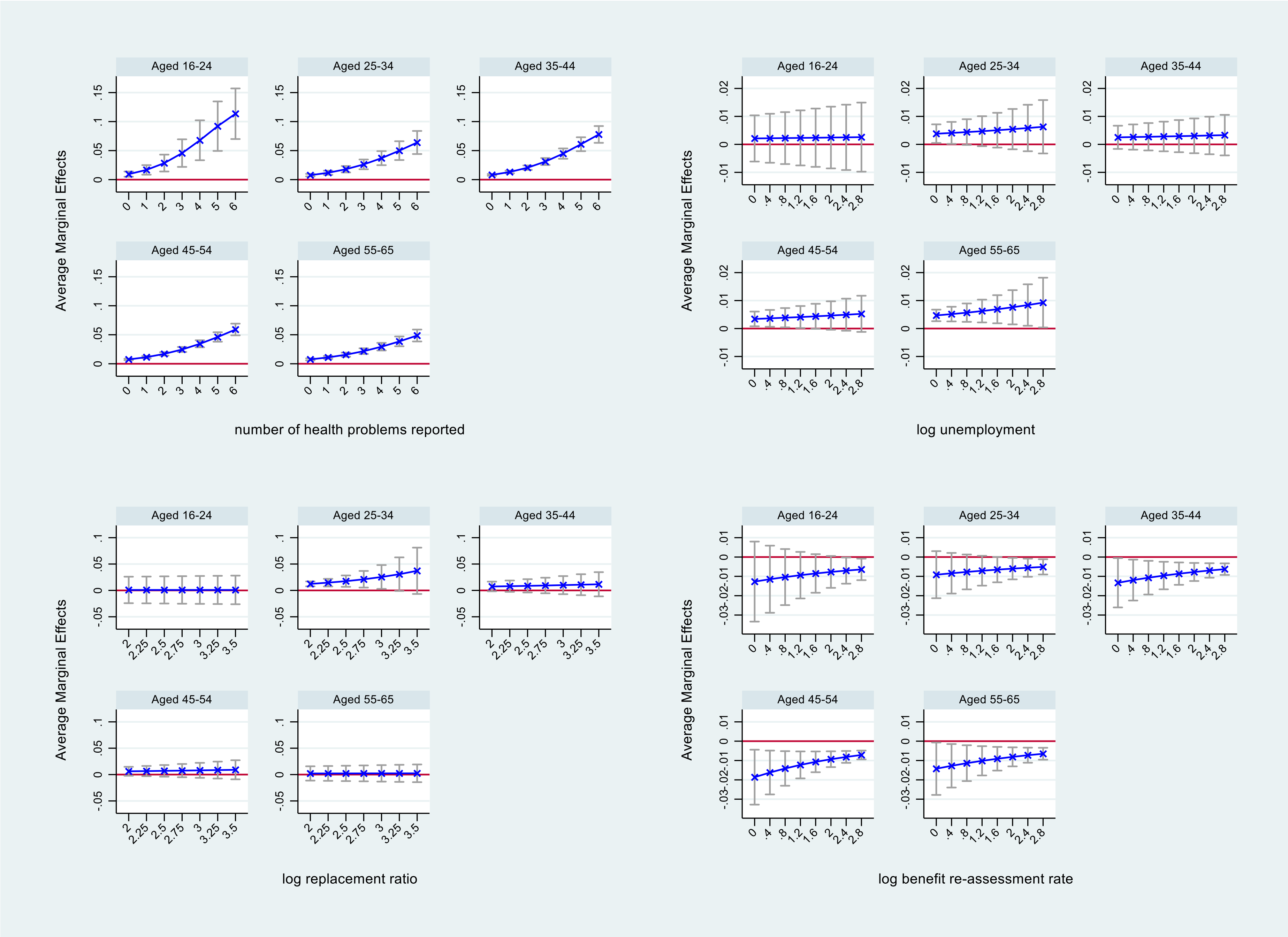
Notes: (i) the vertical axis in each sub-plot shows the average marginal effect upon the probability of claiming ESA; (ii) 95 percent confidence intervals are shown in grey; and (iii) each sub-plot adds a reference line in red on the vertical axis at zero as we are looking for effects that are different to zero.

FIGURE 7: Heterogeneity – government office regions (model 5)



Notes: (i) the vertical axis in each sub-plot shows the average marginal effect upon the probability of claiming ESA; (ii) 95 percent confidence intervals are shown in grey; and (iii) each sub-plot adds a reference line in red on the vertical axis at zero as we are looking for effects that are different to zero.

FIGURE 8: Heterogeneity – age groups (model 6)



Notes: (i) the vertical axis in each sub-plot shows the average marginal effect upon the probability of claiming ESA; (ii) 95 percent confidence intervals are shown in grey; and (iii) each sub-plot adds a reference line in red on the vertical axis at zero as we are looking for effects that are different to zero.