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Roberts, J. and Taylor, K. orcid.org/0000-0002-6525-0815 (2022) New evidence on disability benefit claims in Britain : the role of health and the local labour market. *Economica*, 89 (353). pp. 131-160. ISSN 0013-0427

<https://doi.org/10.1111/ecca.12382>

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New Evidence on Disability Benefit Claims in Britain: The Role of Health and the Local Labour Market

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Final version received 25 May 2021.

During the 1980s and 1990s, there was a steep rise in disability benefit claims in Britain, especially among older male workers, and the debate centred on the relative generosity of these benefits as well as the effects of deindustrialization. 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 labour market has also evolved, and until the recent Covid-19 pandemic, it had a historically low level of unemployment, accompanied by falling real earnings. We use individual longitudinal data from 2010 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 British 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 still influences the propensity to claim those disability benefits that are conditional on not working.

INTRODUCTION

During the 1980s and 1990s, there was a steep rise in disability claims in Britain, 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 deindustrialization 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.¹ At the same time, the labour market has also evolved, and until the recent Covid-19 pandemic, it had been characterized by a historically low level of unemployment accompanied by falling real earnings (Costa and Machin 2017).² Furthermore, the health of the working-age population has continued to deteriorate. The proportion 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 on both the demand side and the supply side, and in particular there is a large amount of variation in both individual circumstances and labour market conditions across Britain. In 2016, the proportion of the working-age population claiming Employment and Support Allowance (ESA)—the UK equivalent of Disability Insurance (DI) in the USA—was lowest in the South East of England at 4.4%, rising to 7.9% and 8.2% in the North East and Wales, respectively.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. 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.⁵ 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.⁶ This means that while disability benefit rates are set nationally, the benefit replacement ratio varies a lot geographically (see below). 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* health (as opposed to *good*, *fair* or *bad*) varied from 44% in the North East to 50% in the South East. In the 2011 Census, 2.7% of working-age people in the South East reported that their day-to-day activities were limited a lot by their health, compared to 5.1% in the North East.⁷

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, gender, 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 genders (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.⁸

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 British labour market. We make the following main contributions to the literature. First, we use individual longitudinal data from 2010 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).⁹ Second, we focus on geographic variation in claims because this is an important and persistent feature but it is under-researched compared to the amount of evidence on the growth of disability benefit rolls over time (McVicar 2006). Third, unlike the majority of existing studies that 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 and type of health problem. Fourth, we use a broader set of health measures than has typically 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 Britain, which is a key contribution given the substantial economic changes brought about by the Great Recession (for example, see Blundell et al. 2014), the ongoing reforms to the disability benefit system (for example, see Banks et al. 2015), and the scale of recent changes in the factors determining disability benefit claims, on both the demand side and the supply side. Our results show that while health status is clearly important, geographic variation in labour market conditions—in particular the local unemployment rate—influences the propensity to claim those disability benefits that are conditional on not working. We also consider the implications of our results for the Covid-19 unemployment forecast made recently by the Office for Budget Responsibility.

I. 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 remain high. There are around three times as many people on disability benefits as on unemployment benefits, and government expenditure on them in 2016–17 was £29 billion—around 1.8% of GDP.¹⁰ The UK is not alone in this. In 2017, spending on disability benefits stood at 2% of GDP on average across the OECD, rising to 4.4% in Norway and 4.9% in Denmark (see OECD 2019).

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 (Bryan et al. 2020). The current government has pledged to narrow this disability employment gap substantially and reduce the disability benefits caseload (DWP 2017a). Partly, this is a response to recessionary pressures and the need to limit the fiscal burden of social security provision. However, it is also recognized that work is key to reducing poverty and 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 they are purely a result of individual health problems (a supply-side issue), or whether they are also a response to labour market conditions and the relative attractiveness of benefits (which both relate to the demand side).¹¹ 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 20th century, there are only a small number of studies that consider geographic variation in these claims. 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 higher in the North and Wales.

McVicar (2006) provides an excellent review of the existing literature, on which we rely here, providing updated evidence where relevant, since most of the reviewed studies use data only up to the 1990s. The first possible contributory factor is spatial variation in health, which might be partly a result of variation in demographic and socioeconomic factors, like age and deprivation (O’Leary et al. 2005; Molho 1989, 1991), and partly due to regional concentrations of the types of heavy industry associated with occupational ill-health (Beatty et al. 2000; Beatty and Fothergill 1996). Figure 2 shows geographic variation in the number of health problems reported by LADs; these are found to be lower on average in the South East, and higher in parts of Scotland, South Wales and Cornwall.

Second, older evidence suggests that the geographic variation in claims was greater than that predicted by variation in health and disability alone, with a consensus that local labour market conditions were also important. A number of studies have demonstrated the significance of local unemployment rates (Disney and Webb 1991; Holmes and Lynch 1990). Beatty and Fothergill (2005) show that the number of people claiming incapacity benefits was greater in the old industrial areas characterized by high unemployment. Beatty et al. (2017) update this analysis with data for 2016 and show that little has changed.¹² The map in Figure 3 shows how unemployment rates vary across LADs, with unemployment higher in the North and Midlands, and parts of South Wales.

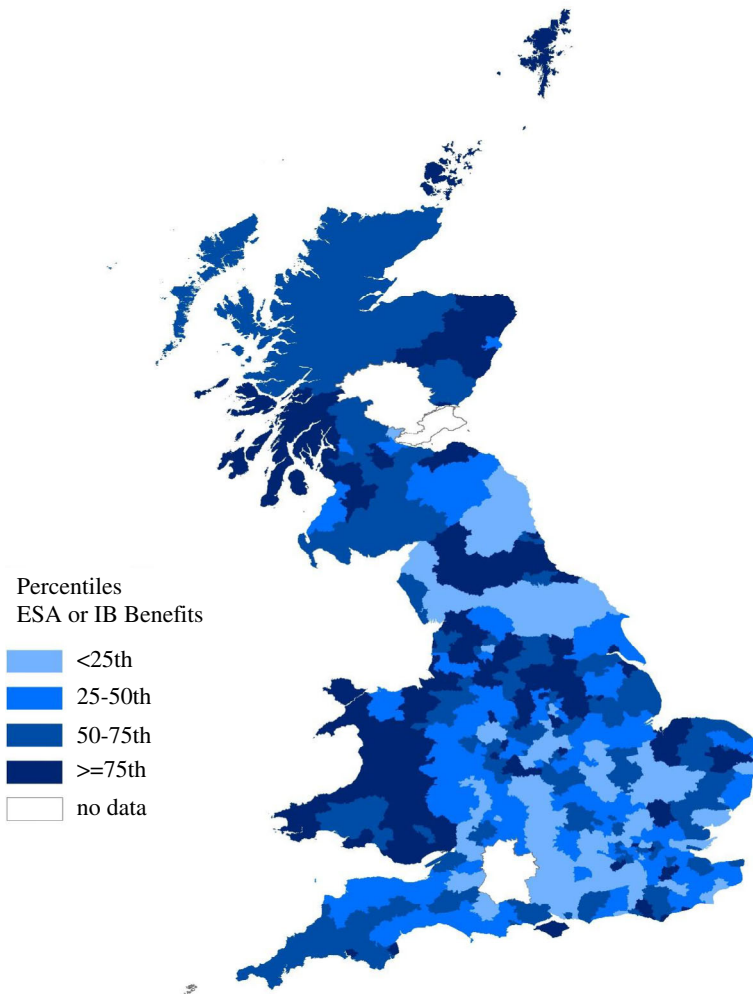


FIGURE 1. Claimant rates by quartile. *Notes:* Produced in ArcGIS using NOMIS data. The claimant rate is the number of ESA or IB claimants as a percentage of the LAD population aged 16–65. Figure based on averages over the period 2010 to 2018.

Finally, the relative attractiveness of disability benefits at a local level may also explain geographic variation in claims.¹³ While benefit rates are set nationally, regional wages vary substantially, and in lower-wage areas, disability benefits are relatively more attractive. They are also more attractive to those workers who can command only low wages due to their individual human capital endowments, but to date there is very little evidence on this. Some older evidence supports 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

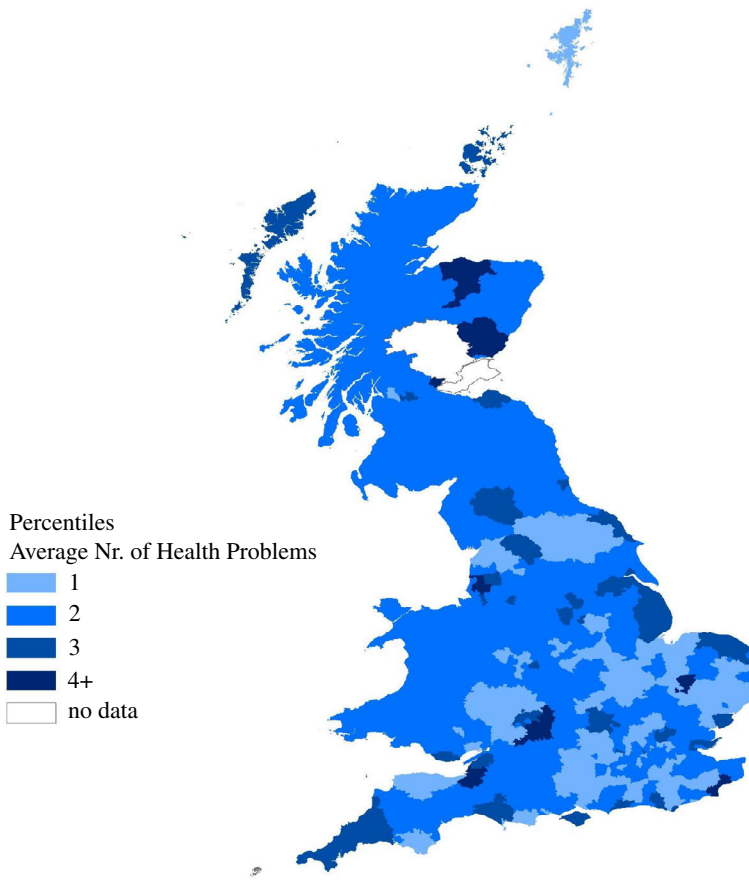


FIGURE 2. Average number of health problems. *Notes:* Produced in ArcGIS using UKHLS data. Health problems are defined according to problems with activities of daily living. Figure based on averages over the period 2010 to 2018.

lower replacement ratios especially for workers towards the bottom end of the wage distribution. Figure 4 shows the variation in benefit replacement ratios across LADs (as a percentage of the local gender-specific median wage). The ratio is highest in the South West, Wales, Lincolnshire and North Norfolk.

II. HEALTH-RELATED BENEFITS

During the period of our analysis there were two main types of benefits available to working-age people with a disability or health problem. First, there are benefits such as the Disability Living Allowance (DLA) 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; it was replaced in 2012 by the Personal Independence Payment (PIP). PIPs are non-means-tested, but require regular work capability assessments (see below); receipt of a PIP, however, is not conditional on not working.¹⁴ Second, there are incapacity benefits, such as the Employment and Support Allowance (ESA), which provide support to those

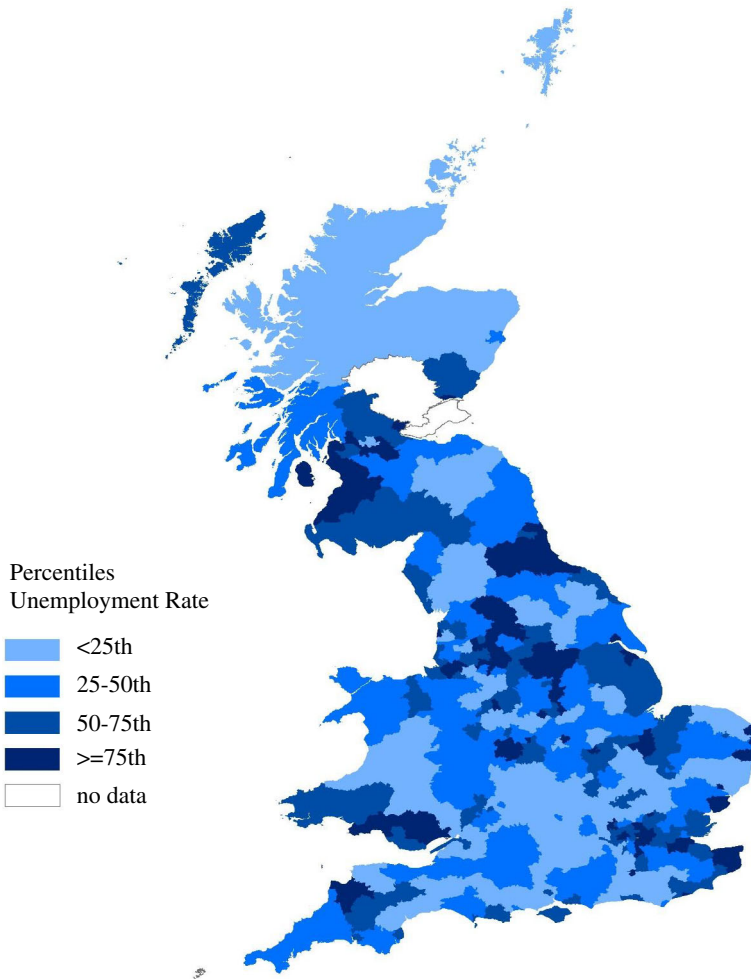


FIGURE 3. Unemployment rate by quartile. *Notes:* Produced in ArcGIS using NOMIS data. Figure based on averages over the period 2010 to 2018.

who cannot work due to their health. About two-thirds of government spending on disability benefits goes on these latter benefits; they are the focus of this paper. ESA was introduced in 2008 to replace Incapacity Benefit (IB).¹⁵ 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).¹⁶ 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 Work Capabilities Assessment (WCA), which is carried out by an external provider and determines whether or not the

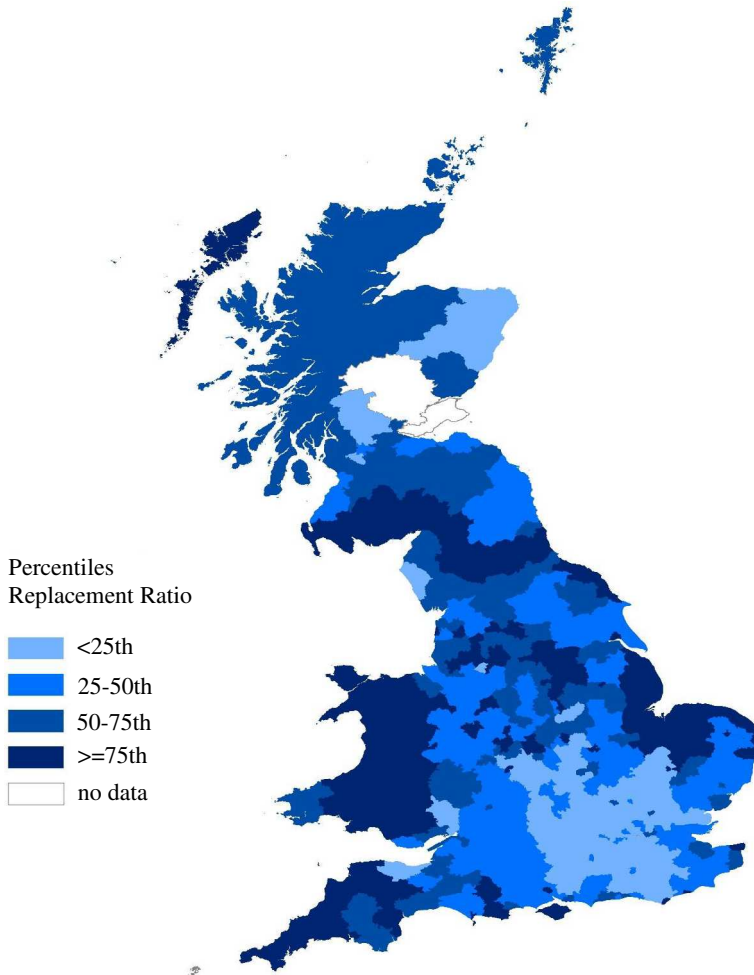


FIGURE 4. Benefit replacement ratio by quartile. *Notes:* Produced in ArcGIS using NOMIS data. The benefit replacement ratio is the average level of disability benefits as a percentage of the local gender-specific average median wage. Figure based on averages over the period 2010 to 2018.

claimant can carry out a set of physical and cognitive activities, based on a list of Activities of Daily Living questions.¹⁷ 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).¹⁸

III. DATA AND METHODOLOGY

We use the first nine waves of *Understanding Society*—the UK Household Longitudinal Study (UKHLS), University of Essex (2019)—a nationally representative longitudinal survey of the UK population that 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 licence 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 on which we focus is 33,350 individuals who are currently of working age (i.e. aged 16 to state pension age¹⁹) and are either in paid employment, unemployed, or long-term sick or disabled, who resided in the same residence in each wave (i.e. we exclude movers—around 7% of individuals).²⁰ These individuals are observed six times on average, yielding an unbalanced panel of 121,190 observations. The UKHLS has information on whether the individual claimed benefits—specifically Incapacity Benefit (IB), Employment and Support Allowance (ESA), Personal Independence Payment (PIP) or Disability Living Allowance (DLA). We have detailed information on the LAD in which the individual resides, which allows us to merge in proxies for local labour market conditions.²¹ Table 1 shows a transition matrix of benefit status. Clearly, most of the sample (92%) are not in receipt of health-related benefits. The lead diagonal shows that the majority of individuals remain in the same state as in the previous period; 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 the probability of receiving either ESA or IB (4.9%) and the likelihood of claiming only PIP/DLA benefits (3%). PIP/DLA claims are not dependent on working status, and an individual may be in receipt of both ESA/IB and PIP/DLA. In our data, 31% claim both ESA/IB and PIP/DLA, 31% are ESA claimants only, and 38% claim PIP/DLA only.^{23,24}

Defining $i = 1, 2, \dots, 33,350$ and $t = 2, 3, \dots, 9$ to denote the individual and the time period, respectively,²⁵ we model the probability of being on benefits (b_{it}) by type (ESA/IB, PIP/DLA) in a dynamic framework that is a correlated random effects (CRE) approach with the incorporation of a lagged dependent variable (see Wooldridge 2005, 2010):

$$b_{it} = 1 \left(\gamma b_{it-1} + \mathbf{X}'_{it} \boldsymbol{\beta} + \sum_{j=1}^J \sum_{g=1}^G \phi_j \{ H_{jit} \times S_{git} \} + \sum_{k=1}^2 \sum_{g=1}^G \psi_k \{ U_{krt-1} \times S_{git} \} + \theta_t + \alpha_i + \varepsilon_{it} > 0 \right) \\ = 1 (\mathbf{Z}'_{it} \boldsymbol{\delta} + \theta_t + \alpha_i + \varepsilon_{it} > 0),$$

$$(1B) \quad \alpha_i = \alpha_0 + \alpha_1 b_{i0} + \mathbf{Z}'_{i0} \boldsymbol{\pi} + \omega_i.$$

TABLE 1
TRANSITION MATRIX OF BENEFIT STATUS

	<i>t</i>			
	ESA	IB	PIP/DLA	No benefits
<i>t</i> – 1				
ESA	72.44%	2.40%	8.10%	17.06%
IB	21.60%	45.43%	14.18%	18.79%
PIP/DLA	12.22%	5.71%	62.26%	19.81%
No benefits	0.91%	0.22%	0.82%	98.04%
	3.74%	1.16%	3.00%	92.10%

Notes

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.

A dynamic specification is appropriate given the strong persistence in disability benefit claims found in the literature (e.g. Berthoud 2004). We condition on a set of covariates 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 in the previous year U_{krt-1} . The latter controls are defined across two variables $k=1, 2$, specifically the local unemployment rate and the local disability benefit replacement ratio (level of benefits as a percentage of the local gender-specific median wage), with each defined at the LAD level ($r=1, 2, \dots, 376$). We also interact the key covariates with binary indicators S_{git} , defining a number of states—for example, gender (where $G=2$) or age group (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, $S_{it}=1$ for all i .

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 PIP/DLA 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 that will result in inconsistent estimates. We follow Wooldridge (2005) and specify the fixed effect in equation (1A) conditional on the initial state b_{i0} , that is, 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, $\bar{Z}_i \ni (\bar{X}_i, \bar{U}_{kr}, \bar{H}_{ji})$, as shown in equation (1B). Substitution of equation (1B) into equation (1A) yields an augmented CRE 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, that is, 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, that is, $\phi_j > \psi_k$ or vice versa. Note also that in further analysis reported below, we adopt a generalized method of moments (GMM) approach, which relaxes the assumptions that health is exogenous and labour market conditions are predetermined, and instead allows for the likelihood that making a benefit claim, local labour conditions and an individual's health are all potentially jointly determined and endogenous covariates.

In the vector 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, 25–34, 35–44 or 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, 3–4, 5–11 and 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, that is, 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; 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 X_{it} are given in Table 2 for the estimation sample, where: just under half the sample are male; 32% are aged 45–54; 27% have a degree as their highest educational qualification; the majority of households own

TABLE 2
SUMMARY STATISTICS—INDIVIDUAL, HOUSEHOLD AND LOCAL AUTHORITY DISTRICT CONTROLS

	Mean	S.D.	Min	Max
<i>Individual and household, X_{it}</i>				
Male	0.482	0.499	0	1
White	0.808	0.394	0	1
Immigrant	0.002	0.044	0	1
Aged 16–24	0.051	0.221	0	1
Aged 25–34	0.162	0.368	0	1
Aged 35–44	0.260	0.439	0	1
Aged 45–54	0.323	0.468	0	1
Number of adults	2.429	1.075	1	12
Number of children 0–2	0.090	0.310	0	5
Number of children 3–4	0.078	0.281	0	3
Number of children 5–11	0.320	0.637	0	5
Number of children 12–15	0.197	0.466	0	5
Degree	0.265	0.441	0	1
Other high	0.102	0.303	0	1
A level	0.079	0.269	0	1
AS level	0.009	0.095	0	1
GCSE	0.201	0.401	0	1
Other qualifications	0.070	0.254	0	1
Married	0.536	0.499	0	1
Home owned outright	0.196	0.397	0	1
Mortgage with equity	0.502	0.500	0	1
Mortgage negative equity	0.032	0.176	0	1
Urban area	0.811	0.392	0	1
North East	0.040	0.195	0	1
North West	0.111	0.314	0	1
Yorkshire	0.093	0.291	0	1
East Midlands	0.078	0.268	0	1
West Midlands	0.091	0.288	0	1
East of England	0.085	0.279	0	1
South East	0.114	0.317	0	1
South West	0.079	0.269	0	1
Wales	0.076	0.266	0	1
Scotland	0.091	0.287	0	1
<i>Local authority district (LAD), U_{rt}</i>				
Unemployment rate, UE (%)	6.801	2.909	1.200	18.901
Replacement ratio, RR (%)	16.562	3.247	4.780	30.176
Number of individuals (N)		25,855		
Observations (NT)		87,840		

their own home via a mortgage with equity, although 3.2% have negative equity; and 81% live in an urban area. The unemployment rate and benefit replacement ratio both display large ranges, reflecting the variation shown in Figures 3 and 4. For example, the average unemployment rate ranges from 1.2% in Aylesbury in 2018 to 18.9% in Thanet in 2012. Also, the replacement ratio is typically found to be higher in the low wage areas of Wales, Cornwall, the East of England and Scotland. In the empirical analysis, the local labour market covariates are included as natural logarithms.

In terms of an individual's health state H_{jit} , this is defined in a number of alternative ways. First, following Banks et al. (2015), we construct three binary indicators ($J=3$) for whether health problems are mild, moderate or severe, based on 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. Second, 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; recognizing when in physical danger; physical coordination; personal care; any other type of health problem. The omitted category is no health problem. Third, rather than conditioning on the type of ADL problem, we control for the number of problems reported ($J=1$). Fourth, 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. This is arguably a more objective measure of health as it is based on the individual's response as to whether they have been explicitly diagnosed with a condition by a doctor. 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 answers to the twelve questions into two summary scores, resulting in a continuous scale with a range of 0 (low functioning) to 100 (high functioning) for both mental and physical health. Table 3 provides summary statistics for each of the alternative health measures. Approximately 6% of individuals have mild ADL problems, compared to 1.6% who have severe problems; just under 17% have an ADL problem, where the mean number of health problems is 0.4. The most prevalent health problems are associated with lifting and mobility at 9.5% and 8.8%, respectively. Around 13% report a specific health condition, with the mean number of health conditions equal to 0.19.

IV. RESULTS

Each of the tables that follow shows the results of estimating CRE dynamic probit models (equations (1A) and (1B)) for the different types of benefit claims. All tables comprise two columns, containing average marginal effects (AMEs) and heteroscedastic consistent robust t -statistics in parentheses for the probability of receiving: (i) ESA or IB; (ii) PIP or DLA. Table 4 reports full results for all variables (excluding region), with the first 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 and benefits replacement ratio (each lagged by one year)—and individual health defined in

TABLE 3
SUMMARY STATISTICS—HEALTH CONTROLS

	Mean	S.D.	Min	Max
Banks et al. (2015), $H_{jit}(J=3)$				
Health mild	0.058	0.233	0	1
Health moderate	0.023	0.148	0	1
Health severe	0.016	0.127	0	1
<i>Health problems, $H_{jit}(J=11)$</i>				
Mobility	0.088	0.283	0	1
Lifting, carrying or moving objects	0.095	0.293	0	1
Manual dexterity	0.040	0.195	0	1
Continence	0.025	0.157	0	1
Hearing	0.016	0.126	0	1
Sight	0.017	0.131	0	1
Communication or speech	0.012	0.110	0	1
Memory or ability to concentrate	0.043	0.202	0	1
Recognizing physical danger	0.008	0.088	0	1
Physical coordination	0.035	0.184	0	1
Personal care	0.028	0.166	0	1
Other type of problem	0.009	0.096	0	1
<i>Health problems, $H_{jit}(J=1)$</i>				
Number of health problems, H_{it}	0.398	1.128	0	6
<i>Health conditions, $H_{jit}(J=1)$</i>				
Number of health conditions ^{a,a} , H_{it}	0.190	0.579	0	6
<i>Short Form 12 generic health instrument, $H_{jit}(J=2)$</i>				
SF-12 physical health summary score	45.836	18.262	0	74.17
SF-12 mental health summary score	43.261	17.490	0	76.12
Number of individuals (N)		25,855		
Observations (NT)		87,840		

Notes

^aThe number of health conditions comprises a count of the whether the individual has any of the following: asthma (0.046), arthritis (0.024), diabetes (0.012), blood pressure (0.040), depression (0.025), and any other health condition (0.016), with the mean given in parentheses.

line with Banks et al. (2015) as the presence of mild, moderate or severe health problems according to the ADL questions. As expected, in both columns health is a key determinant of disability benefit claims, with a clear gradient across severity of problems. Specifically, having mild health problems increases the probability of claiming ESA/IB by around 1.5 percentage points (pp), compared to having no health problems, increasing to 2.0 pp and 2.5 pp for moderate and severe problems, respectively. For ESA/IB, a higher local unemployment rate increases the propensity to claim—there are no effects stemming from the benefit replacement ratio. For example, a doubling of the unemployment rate would increase the probability of making an ESA/IB claim by 0.54 pp. 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 are clearly important for the likelihood of claiming ESA/IB, local labour market conditions are also still a relevant contributory factor, and we return to the relative importance of these effects below.²⁶

Consistent with the findings of Berthoud (2004) and Emmerson et al. (2017), there is clear evidence of persistence in the probability of benefit receipt, with those making an

TABLE 4
DYNAMIC PROBABILITY MODELS—HEALTH, BASED ON BANKS ET AL. (2015)

	ESA/IB		PIP/DLA	
ESA/IB _{<i>t</i>-1}	0.0486	(21.71)		
PIP/DLA _{<i>t</i>-1}			0.0531	(23.04)
log UE _{<i>t</i>-1}	0.0054	(2.03)	0.0004	(0.17)
log RR _{<i>t</i>-1}	0.0026	(0.26)	0.0084	(0.91)
Mild	0.0152	(7.78)	0.0127	(7.05)
Moderate	0.0204	(7.54)	0.0235	(8.92)
Severe	0.0254	(7.39)	0.0276	(7.91)
Male	0.0007	(0.46)	-0.0048	(3.07)
White	-0.0040	(2.45)	0.0024	(1.56)
Immigrant	0.0116	(1.48)	-0.0001	(0.02)
Aged 16–24	-0.0003	(0.04)	-0.0065	(0.81)
Aged 25–34	-0.0001	(0.02)	-0.0110	(2.01)
Aged 35–44	0.0001	(0.02)	-0.0046	(1.20)
Aged 45–54	0.0005	(0.21)	-0.0059	(2.35)
Number of adults	-0.0019	(1.52)	-0.0011	(0.94)
Number of children 0–2	0.0030	(1.03)	-0.0003	(0.11)
Number of children 3–4	0.0052	(1.65)	0.0020	(0.77)
Number of children 5–11	-0.0012	(0.49)	0.0021	(1.03)
Number of children 12–15	-0.0013	(0.59)	0.0053	(2.81)
Degree	0.0002	(0.01)	0.0193	(1.70)
Other high	-0.0085	(0.89)	0.0089	(0.97)
A level	-0.0137	(0.86)	0.0202	(1.06)
AS level	0.0111	(1.00)	0.0104	(1.45)
GCSE	-0.0079	(0.51)	0.0100	(0.82)
Other qualifications	0.0179	(1.58)	0.0080	(0.52)
Married	-0.0061	(1.95)	0.0151	(5.18)
Home owned outright	0.0073	(1.47)	0.0001	(0.04)
Mortgage with equity	-0.0017	(0.40)	-0.0007	(0.20)
Mortgage negative equity	0.0049	(0.87)	0.0030	(0.60)
Urban area	0.0026	(1.54)	0.0038	(2.54)
2013	-0.0037	(1.27)	-0.0001	(0.63)
2014	0.0022	(2.19)	0.0043	(2.68)
2015	0.0061	(3.37)	0.0075	(4.49)
2016	0.0050	(2.63)	0.0077	(4.17)
2017	0.0051	(2.38)	0.0109	(5.27)
2018	0.0041	(2.59)	0.0094	(3.79)
Wald $\chi^2(70)$; <i>p</i> -value	6042.79; <i>p</i> = 0.000	7043.39; <i>p</i> = 0.000		
ρ ; <i>p</i> -value	0.3435; <i>p</i> = 0.000	0.2810; <i>p</i> = 0.000		
<i>N</i>		25,855		
<i>NT</i>		87,840		

Notes

Other controls include region dummies, the mean of time-varying covariates, and the initial observed benefit state. Average marginal effects are reported, along with heteroscedastic robust *t*-statistics in parentheses.

ESA/IB claim in the previous year being 4.9 pp more likely to make a claim in the current year. The level of persistence in PIP or DLA claims is larger than that found for ESA/IB, and the health effects are also marginally larger. 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/IB claims. The exceptions are that being white and married both decrease the likelihood of claiming ESA/IB, and being male and aged 25–34 or 45–54 reduce the likelihood of being on PIP/DLA; while having children aged 12–15, being married and living in an urban area all increase the likelihood of receiving this type of benefit.

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

TABLE 5
DYNAMIC PROBABILITY MODELS—HEALTH PROBLEMS

	ESA/IB		PIP/DLA	
<i>Panel A: Type of problem</i>				
ESA/IB _{<i>t</i>-1}	0.0475	(21.80)		
PIP/DLA _{<i>t</i>-1}			0.0526	(22.60)
log UE _{<i>t</i>-1}	0.0051	(1.98)	0.0002	(0.09)
log RR _{<i>t</i>-1}	0.0005	(0.05)	0.0083	(0.90)
Mobility	0.0078	(3.54)	0.0101	(5.14)
Lifting, carrying, moving objects	0.0082	(3.88)	0.0088	(4.48)
Manual dexterity	0.0015	(0.64)	0.0048	(2.07)
Continence	0.0025	(0.89)	0.0055	(1.93)
Hearing	-0.0031	(0.78)	-0.0027	(0.76)
Sight	0.0012	(0.37)	0.0026	(0.80)
Communication or speech	0.0023	(0.68)	0.0038	(0.99)
Memory/ability to concentrate	0.0056	(2.62)	0.0034	(1.47)
Recognizing physical danger	-0.0008	(0.19)	-0.0012	(0.27)
Physical coordination	0.0054	(2.18)	0.0047	(1.82)
Personal care	0.0029	(1.11)	0.0045	(1.64)
Other type of health problem	0.0070	(1.92)	0.0031	(0.75)
Wald $\chi^2(88)$; <i>p</i> -value	5799.23; <i>p</i> = 0.000	6710.97; <i>p</i> = 0.000		
ρ ; <i>p</i> -value	0.3387; <i>p</i> = 0.000	0.2846; <i>p</i> = 0.000		
<i>N</i>		25,855		
<i>NT</i>		87,840		
<i>Panel B: Number of problems</i>				
ESA/IB _{<i>t</i>-1}	0.0491	(21.88)		
PIP/DLA _{<i>t</i>-1}			0.0525	(22.66)
log UE _{<i>t</i>-1}	0.0053	(2.03)	0.0003	(0.12)
log RR _{<i>t</i>-1}	0.0034	(0.34)	0.0084	(0.91)
Number of health problems	0.0056	(9.88)	0.0059	(11.03)
Wald $\chi^2(66)$; <i>p</i> -value	5873.92; <i>p</i> = 0.000	6543.36; <i>p</i> = 0.000		
ρ ; <i>p</i> -value	0.3402; <i>p</i> = 0.000	0.2875; <i>p</i> = 0.000		
<i>N</i>		25,855		
<i>NT</i>		87,840		

Notes

See Table 4.

dichotomous variables, whereas in panel B the number of problems is used as a proxy for the severity of the health state. The control variables are omitted from the table for conciseness. As with severity of ADL problems in Table 4, the only local labour market effects stem from the unemployment rate having a significant effect on the propensity to claim ESA/IB 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 other unspecified health problems all increase the propensity to claim ESA/IB. Those individuals who report problems with mobility, lifting, manual dexterity, continence and physical coordination also have a higher probability of claiming PIP/DLA. Focusing on ESA/IB, the largest health effect stems from lifting, where having this specific health problem increases the probability of claiming ESA by 0.8 pp. Turning to the number of health problems in panel B, the propensity to claim ESA/IB or PIP/DLA increases with the number of problems by about 0.6 pp for each additional health problem.

Table 6 is an equivalent model to Table 5 but measuring health via the number of specific health conditions that a respondent reports. The number of conditions is not statistically significant for claiming any benefits, probably because most are chronic conditions and hence display little change over time so are netted out in a CRE framework.²⁷ A higher local unemployment rate increases the propensity to claim ESA/IB, as does a higher benefit replacement ratio. As expected, the labour market variables are again 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/IB, but the size of the effect is very small, clearly dominated in terms of magnitude by local labour market conditions, where the only significant effect is from the unemployment rate. While better physical health reduces the propensity to claim ESA/IB and PIP/DLA, better mental health increases the likelihood of receiving PIP/DLA. This implies that people with poor mental health are more likely to end up on 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 is clearly an important determinant of the propensity to claim both ESA/IB and PIP/DLA, local labour market

TABLE 6
DYNAMIC PROBABILITY MODELS—HEALTH CONDITIONS

	ESA/IB		PIP/DLA	
ESA/IB _{<i>t-1</i>}	0.0631	(21.84)		
PIP/DLA _{<i>t-1</i>}			0.0799	(25.74)
log UE _{<i>t-1</i>}	0.0064	(2.33)	0.0016	(0.43)
log RR _{<i>t-1</i>}	0.0019	(1.88)	0.0149	(1.69)
Number of health conditions	-0.0007	(0.61)	-0.0006	(0.02)
Wald $\chi^2(66)$; <i>p</i> -value	6572.84; <i>p</i> = 0.000	8816.17; <i>p</i> = 0.000		
ρ ; <i>p</i> -value	0.3994; <i>p</i> = 0.000	0.2723; <i>p</i> = 0.00		
<i>N</i>		25,855		
<i>NT</i>		87,840		

Notes

See Table 4.

TABLE 7
DYNAMIC PROBABILITY MODELS—SF-12 PHYSICAL AND MENTAL HEALTH

	ESA/IB		PIP/DLA	
ESA/IB _{<i>t</i>-1}	0.0606	(23.36)		
PIP/DLA _{<i>t</i>-1}			0.0760	(27.20)
log UE _{<i>t</i>-1}	0.0076	(2.78)	0.0017	(0.68)
log RR _{<i>t</i>-1}	0.0127	(1.22)	0.0213	(1.65)
SF-12 physical health	-0.0001	(2.31)	-0.0002	(3.24)
SF-12 mental health	-0.0001	(1.30)	0.0002	(5.38)
Wald $\chi^2(68)$; <i>p</i> -value	6937.70; <i>p</i> = 0.000	8856.87; <i>p</i> = 0.000		
ρ ; <i>p</i> -value	0.3500; <i>p</i> = 0.000	0.2419; <i>p</i> = 0.000		
<i>N</i>		25,855		
<i>NT</i>		87,840		

Notes

See Table 4.

conditions are relevant only for ESA/IB and, as expected, are not important for PIP/DLA claims. These findings are apparent after incorporating a lagged dependent variable, where there is clear evidence of state dependence in each type of benefit claim, and the mean of time-varying covariates (including health) in a CRE framework that approximates a fixed effects estimator.²⁸

Endogeneity

So far, we have treated health as exogenous and labour market conditions as predetermined (by entering them as a lag); we now investigate whether the results hold when treating these covariates as endogenous. For instance, the likelihood of making a benefit claim, local labour market conditions and an individual's health are all potentially jointly determined. In order to consider this potential endogeneity, we estimate a linear probability model by GMM, focusing on the number of ADL health problems reported (as this is a continuous variable).²⁹ We employ a system GMM approach (Arellano and Bover 1995; 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/IB and PIP/DLA, the Sargan test that the over-identifying restrictions are valid cannot be rejected at conventional levels of statistical significance, 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. After treating health as an endogenous variable we still find that the number of health problems increases the likelihood of claiming each benefit type (as found in panel B of Table 5). Moreover, local labour market effects stemming from unemployment still remain and as expected influence only ESA/IB claims. Hence in terms of sign and statistical significance, the GMM estimates concur with our previous findings.

Comparing the economic magnitude between the average marginal effects estimated in the CRE probit models (panel B of Table 5) and GMM analysis (Table 8), we find the

TABLE 8
GMM LINEAR PROBABILITY MODEL—HEALTH PROBLEMS

	ESA/IB		PIP/DLA	
ESA/IB _{<i>t</i>-1}	0.2788	(13.48)		
PIP/DLA _{<i>t</i>-1}			0.2790	(10.61)
log UE	0.0255	(2.62)	0.0243	(0.90)
log RR	-0.0288	(0.80)	0.0156	(0.83)
Number of health problems	0.0311	(6.24)	0.0280	(7.48)
Wald $\chi^2(40)$; <i>p</i> -value	487.95; <i>p</i> = 0.000	655.92; <i>p</i> = 0.000		
Test for AR(2) in errors; <i>p</i> -value	1.9239; <i>p</i> = 0.154	-0.4012; <i>p</i> = 0.688		
Test for AR(3) in errors; <i>p</i> -value	-0.3281; <i>p</i> = 0.743	-0.3312; <i>p</i> = 0.742		
Sargan over-identification test $\chi^2(22)$; <i>p</i> -value	35.44; <i>p</i> = 0.156		18.60; <i>p</i> = 0.670	
Number of instruments		84		
<i>N</i>		25,855		
<i>NT</i>		87,840		

Notes

Other controls as in Table 4. 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. Average marginal effects (AMEs) are shown for unemployment, the replacement ratio and the number of health problems. The AMEs are the summation of the contemporaneous and all lagged estimates for each covariate.

following. A doubling of the unemployment rate is associated with an increase in the likelihood of claiming ESA/IB by 0.5 pp in the CRE probit model, compared to 2.6 pp based on the GMM estimates. An additional health problem would increase the probability of making an ESA/IB claim by 0.6 pp in the CRE probit model, compared to 3.1 pp based on the GMM estimates. The difference in the size of the economic magnitude between the estimators is around fivefold and implies that due to potential endogeneity, the CRE probit estimates are likely to be downwardly biased—hence the CRE probit analysis probably underestimates the impact of health and the local labour market on benefit claims.³⁰

Heterogeneity

Having explored endogeneity issues and found that the results are similar to the CRE approach in terms of statistical significance and direction of influence of both health and local labour market effects, we now return to the CRE 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 that no local labour market effects were found for the probability of claiming PIP/DLA, for brevity the focus is now solely on the likelihood of claiming ESA/IB. We interact the effects of health (based on the number of ADL problems as in panel B of Table 5) and the two local labour market variables with: (i) gender; (ii) education level, that is, A level or above, or below A level; and (iii) lifecycle effects (defined by a series of age indicators, as described in Section III). In terms of equation (1A) for gender and education, $G = 2$; while for lifecycle effects based on five age bands, $G = 5$. While 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 (Ai and Norton 2003; 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. 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 for different values of the second variable (e.g. gender), and providing corresponding confidence intervals.

Figure 5 shows the results for gender. Each sub-plot has a horizontal reference line from the vertical axis at zero as we are looking for effects that are different to zero. We provide AMEs for each group—that is, males and females—along with 95% confidence intervals. The effects of health problems are similar across the genders, although the slope of the AMEs across the number of health problems—which indicates the effect on the probability of claiming ESA/IB—is marginally steeper for females. There is some evidence of heterogeneity between the genders in terms of the effect of local labour market conditions on the propensity to claim ESA/IB, where unemployment is associated with a higher probability of benefit

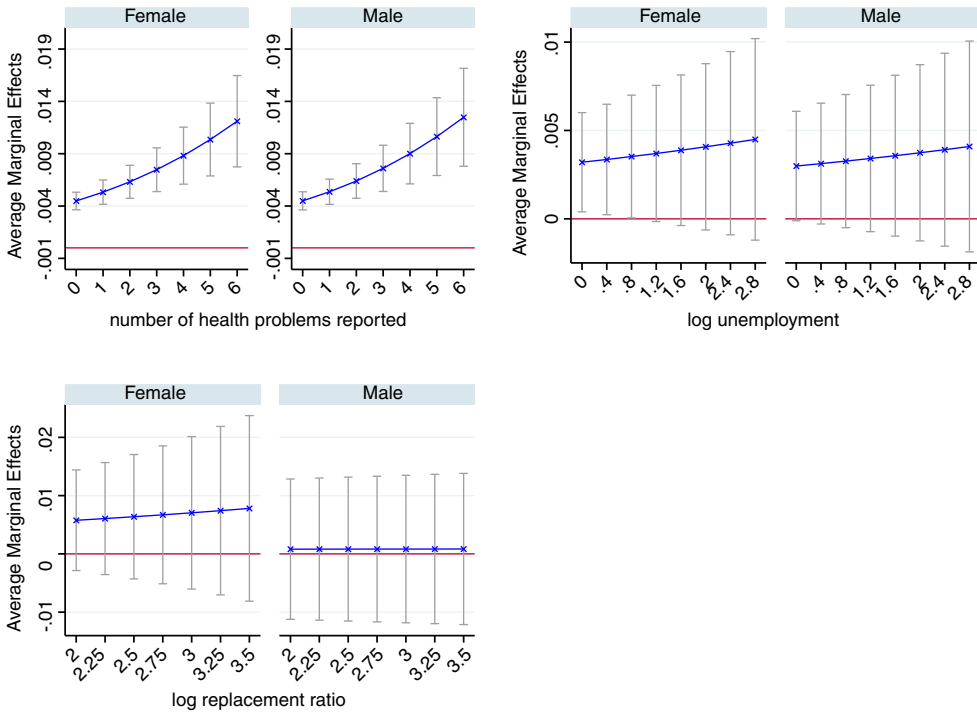


FIGURE 5. Heterogeneity—gender. *Notes:* The vertical axis in each sub-plot shows the average marginal effect on the probability of claiming ESA. 95% confidence intervals are shown in grey. Each sub-plot includes a horizontal reference line from the vertical axis at zero as we are looking for effects that are different to zero.

receipt for females (perhaps reflecting lower attachment to the labour market due to women’s dual labour market and domestic roles).

We now consider whether there are differential effects on the probability of claiming ESA/IB between people with higher (A level and above) and lower (below A level) levels of education (Figure 6). As the number of health problems escalates, those individuals who are more highly qualified noticeably have a greater propensity to claim benefits compared to those with lower educational attainment (culminating in a 2 pp differential). The local unemployment rate has a statistically significant and positive effect on the likelihood of claiming ESA/IB for the lower-educated group.

In Figure 7, we explore whether the effects of health problems and local labour market conditions impact differently on the propensity to claim ESA according to age. Specifically, we consider five age groups, namely 16–24, 25–34, 35–44, 45–54 and 55–65. The upper-left-hand pane considers the number of health problems. For each age band, health problems increase the probability of claiming ESA/IB; this is most apparent for those aged 16–24, where someone with six or more health problems is 4 pp more likely to receive benefits. The upper-right-hand pane considers the local unemployment rate. Clearly, there are differential effects of higher unemployment rates on benefit claims for 55–65-year-olds, increasing the likelihood of ESA/IB benefits by around 1 pp for those living in locations with the highest levels of unemployment. In the lower-left-hand pane, the focus is on the benefit replacement rate. The only statistically significant effects stem from those aged 25–34, with a higher replacement ratio increasing the probability of claiming ESA/IB.

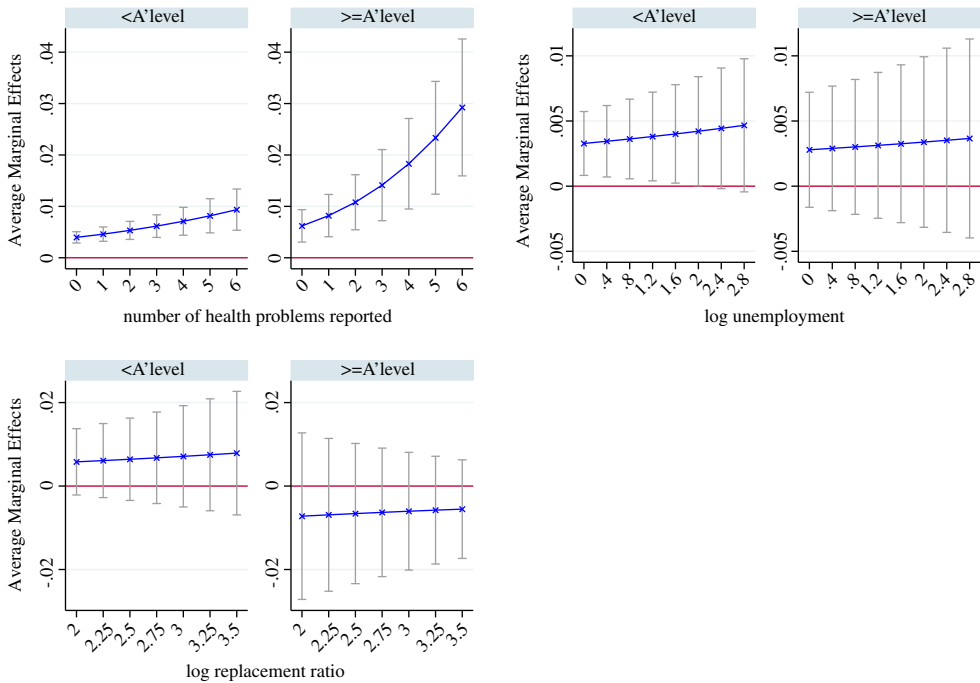


FIGURE 6. Heterogeneity—qualifications. Notes: See Figure 5.

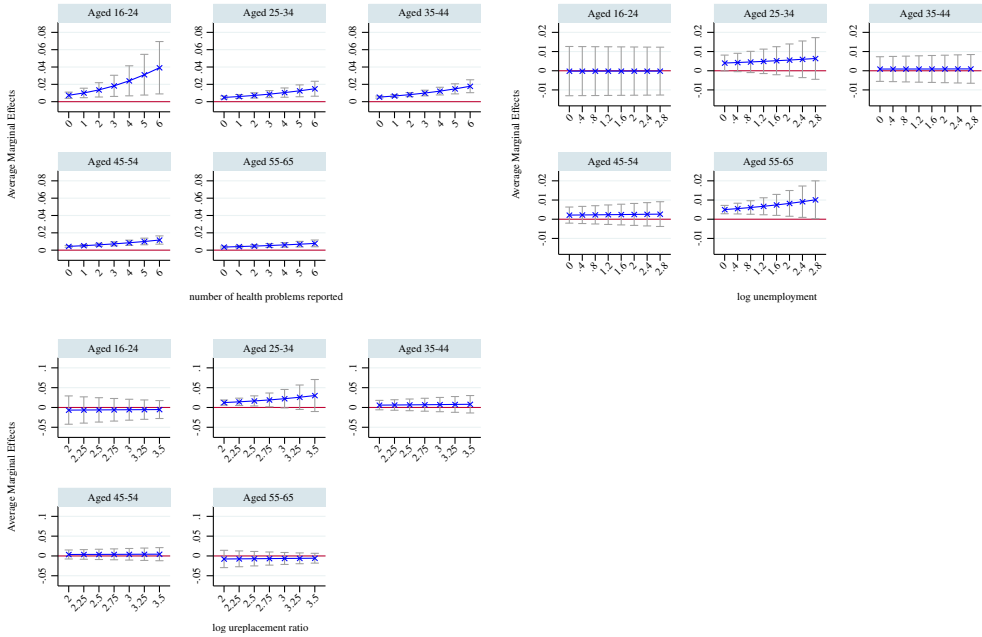


FIGURE 7. Heterogeneity—age groups. *Notes:* See Figure 5.

Differential probability of benefit receipt under alternative states of health and unemployment

We now compare the relative effects of health and unemployment on the likelihood of receiving ESA/IB under a number of different scenarios. At the time of writing in 2021, the UK is facing a global pandemic caused by the coronavirus (Covid-19), which is having severe effects on the economy, hence we also look at forecasts of unemployment rates and how these might influence benefit take-up. To be specific, the scenarios that we investigate are as follows: (A) alternative states of ADL health; (B) changing number of health problems; (C) maximum versus minimum LAD unemployment rates; and (D) the current UK unemployment rate versus the forecast made by the Office for Budget Responsibility (OBR) in the first quarter of 2021.³¹

To do this, we calculate two probabilities based on all common characteristics except for altering the values of key covariates (e.g. health state or unemployment) in order to then generate a differential probability. To be more specific, we calculate the differential probability after estimating equations (1A) and (1B) from the following:

$$(2) \quad \hat{b}^1 - \hat{b}^0 = \left\{ \Phi(\mathbf{Z}^1 \hat{\delta}) - \Phi(\mathbf{Z}^0 \hat{\delta}) \right\}.$$

Hence $(\hat{b}^1 - \hat{b}^0) \times 100\%$ is the differential probability in percentage terms. \mathbf{Z}^1 is a vector of covariates as defined above, but with the same values across all individuals with the exception of one variable, for example, ADL health defined as ‘mild’.³² Then \mathbf{Z}^0 is an identical vector, except that now ADL health problems are set to zero. The parameter estimates from the model are $\hat{\delta}$, and Φ denotes the cumulative normal distribution.

The same approach is adopted to calculate the effects of differential unemployment rates on the likelihood of claiming benefits, where now only the LAD, region and unemployment rate are changed in Z^1 and Z^0 . In each panel of Table 9 we also provide a ‘back of the envelope’ estimate of the increase in the number of ESA/IB claims under each scenario. This is found by multiplying the probability calculated from equation (2) by the number of ESA/IB benefit claimants in 2018.³³

The results of this analysis are shown in Table 9, where there are four panels corresponding to the above scenarios. Focusing on panel A, which considers different ADL health states—i.e. all characteristics are held constant except ADL health—we first consider a mild health state compared to having no ADL problems. This analysis is based on the estimates of Table 4. The resulting differential in the probability of receiving ESA/IB is 7.3% (i.e. nearly 23,000 extra claims among the defined group). Next we compare a moderate health state to that of having no ADL problems, and finally a severe health state relative to no ADL problems, where the differential likelihoods of claiming ESA/IB are 10.7% and 14.5%, respectively. Then in panel B of Table 9, we consider the number of health problems reported compared to having no health problems, where the analysis is based on the estimates of panel B of Table 5. Clearly, there is a monotonic health gradient for the probability of receiving benefits. This starts from 2.1% comparing one health problem to no problems (associated with around 6500 more claims), culminating in a 20% higher chance of claiming benefit for six or more health problems (increasing ESA/IB claims by 63,500).

The remaining panels of Table 9 focus on unemployment. In panel C we compare the differential probability of ESA/IB between the maximum and minimum LAD unemployment rates. This analysis is based on the estimates of Table 4, where we impose common characteristics except the LAD and region of residence. The LAD with the highest unemployment rate in 2018 was Hartlepool in the North East; conversely, the LAD with the lowest unemployment rate was Aylesbury in the South East. The difference in the likelihood of claiming ESA/IB ranges from approximately 6% to 8%, depending on the underlying health state. However, in terms of magnitude, it is clearly much smaller than the onset of health problems—specifically having moderate or severe health problems (relative to no ADL problem), or four or more health problems (relative to no health problems).

In panel D of Table 9, we focus on comparing the current UK unemployment rate of 5% in 2021Q1 to that forecast by the OBR. It is predicted that the annual unemployment rate will increase following the effects of the UK economy lockdown to slow the spread of the coronavirus and the subsequent impact that this will have on industry and ultimately jobs. Here we consider a forecast of unemployment produced by the OBR where the UK unemployment rate is predicted to be 6.5% by the end of 2021.³⁴ Based on the estimates of Table 4, the differential likelihood in claiming ESA/IB under the OBR forecast ranges from 3.6% to 4.5%, depending on the underlying health state, but it is clearly outweighed by the ADL health impacts on the probability of claiming benefits (see panels A and B of Table 9, all relative to having no health problems). This translates into an increase in the number of claimants of around 11,000 to 14,000, depending on the underlying health state. While these increases in claim numbers may seem small, it is worth stressing that this is the increase in the number of claims among females aged 45–54, where this group made up only 14.5% of total claimants in 2018. In this analysis, it is important to realize that the simulations hold under the assumption of time-invariant parameters estimated in the main analysis, hence the results should be interpreted with caution.

TABLE 9
DIFFERENTIAL PROBABILITY OF BENEFIT RECEIPT AND NUMBER OF ESA/IB CLAIMANTS
UNDER ALTERNATIVE STATES OF HEALTH AND UNEMPLOYMENT

Altered variable	Contrast	$(\hat{b}^1 - \hat{b}^0) \times 100\%$	Increase in ESA/IB claims
A: ADL health ^{a,a}	Mild vs. no ADL problems	7.3%	22,842
	Moderate vs. no ADL problems	10.7%	33,480
	Severe vs. no ADL problems	14.5%	45,371
B: Number of health problems ^b	1 vs. no health problems	2.1%	6571
	2 vs. no health problems	4.6%	14,393
	3 vs. no health problems	7.7%	24,093
	4 vs. no health problems	11.3%	35,358
	5 vs. no health problems	15.5%	48,500
	6+ vs. no health problems	20.3%	63,519
C: UE LAD max/min ^c : Hartlepool vs. Aylesbury Vale	Mild health problem	6.2%	19,400
	Moderate health problem	7.2%	22,529
	Severe health problem	8.2%	25,658
	Mild health problem	3.6%	11,264
D: UE OBR Covid-19 scenario ^d : OBR forecast vs. 2021Q1 UE	Moderate health problem	4.0%	12,516
	Severe health problem	4.5%	14,081

Notes

$(\hat{b}^1 - \hat{b}^0) \times 100\%$ is the percentage differential in the probability of receiving ESA/IB under alternative scenarios. Throughout each panel A–D, common characteristics, based on the dominant binary categories from Table 2, are: female; white; non-immigrant; aged 45–54; one adult in the household (excluding respondent); dependent children aged 5–11; degree-level education; married; home owned on mortgage with equity; lives in an urban area; year of interview 2018; and (with the exception of panel C) the region of residence is London. In panels C and D, we undertake the analysis separately for mild, moderate and severe ADL health problems. The figures reported in the final column are found by multiplying $(\hat{b}^1 - \hat{b}^0)$ by the number of female ESA/IB claimants aged 45–54 in 2018 (312,900 based on DWP statistics). Calculations in panels A, C and D are based on the estimates reported in Table 4, while those in panel B are based on the estimates shown in panel B of Table 5. Figures are based on the assumption that benefits were claimed in the previous period.

^aBased on common characteristics except ADL health.

^bBased on common characteristics except the number of health problems.

^cBased on common characteristics except LAD and region of residence.

^dSee <https://obr.uk/efo/economic-and-fiscal-outlook-march-2021> (accessed 29 May 2021); based on common characteristics except LAD unemployment rates where all are increased by the same proportion as indicated in the March 2021 OBR forecast.

These calculations, based on a given set of characteristics, have revealed that both health and unemployment have sizeable effects on the differential likelihood of benefit receipt under the different scenarios considered in Table 9, and potentially on the number of claims. Clearly, extreme health effects (e.g. severe ADL problems or having in excess of three health problems) have a larger impact on the probability of receiving ESA/IB (relative to no health problems) than the calculated impact of differential unemployment rates. However, most individuals in the sample do not have health problems; Table 3 revealed that based on the Banks et al. (2015) measure, approximately

90% of individuals reported no ADL health problem, and the mean number of health problems is just 0.4. Focusing on the unemployment rate, while there is considerable variation across the UK, the average rate is 6.8% over the sample period. Under all scenarios where the effects of unemployment forecasts were calculated (panel D of Table 9), the differential probability of claiming ESA/IB dominated the 2.1% effect found from having one versus no health problems (panel B)—which is arguably the most reasonable estimate given the mean number of health problems. So while moderate and extreme health effects are important, they are arguably driven by, and only relevant to, a small proportion of the UK population, whereas unemployment has a wider societal impact, conceivably affecting more individuals. However, as discussed in the Introduction and Section I, the proportion of the population reporting health problems has increased over time, and there is likely to be a substantial rise in mental health problems as a consequence of Covid-19 (e.g. Brodeur et al. 2020; Banks and Xu 2020). Moreover, there is clear evidence of spatial variation in the number of health problems around the mean (see Figure 2). In summary, the effects of health and unemployment would both appear to be non-negligible under the alternative scenarios that we have considered. With unemployment rates forecast to rise alongside an expected increase in the prevalence of mental health problems, our analysis suggests sizeable impacts on the likelihood of benefit receipt and the number of claimants in the future.

V. CONCLUSION

This paper uses individual longitudinal data from 2010 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 British 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 the local unemployment rate still influences the propensity to claim ESA/IB, but there is little evidence that benefit generosity plays a role. Local unemployment rates vary widely throughout the country, and for example, a female aged 45–54 with mild health problems living in Hartlepool in the North East has a 6% higher chance of claiming ESA benefits than the equivalent female living in Aylesbury in the South East; for a comparable female but who has severe health problems, the differential between the two local authorities rises to 8%. Local labour market 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.

These average effects also mask important heterogeneity by gender, age and education level. There is some evidence that those individuals who are more likely to be economically disadvantaged, i.e. less educated, are the ones who are most adversely affected by local labour market conditions. Individuals in the 55-65 age group are most affected by higher unemployment rates monotonically increasing the probability of claiming ESA/IB. Those individuals aged 16-24 are more likely to claim ESA/IB increasing monotonically in the number health of problems. In summary, it would appear that there are certain groups that are more sensitive to local labour market conditions, in particular the less-educated 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, the government seems to have acknowledged the complexity of the challenge. It has established the cross-department Work and Health Unit to deliver change, and the 2017 White Paper recognizes the complementary roles of the welfare and employment system, healthcare services and employers. Furthermore, 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) describes 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', emphasizing the need to work in partnership with local organizations and devolved administrations to ensure that local needs are met. Our results are timely and suggest that this spatially informed policy is essential.

ACKNOWLEDGMENTS

The UK Household Longitudinal Study (UKHLS) is an initiative by the Economic and Social Research Council, with scientific leadership by the Institute for Social and Economic Research, University of Essex, and survey delivery by the National Centre for Social Research. The data were accessed via the UK Data Service, some of it under Special Licence. We would like to thank the Editor and three anonymous referees for excellent feedback. We are grateful to Mark Bryan, Andy Bryce, Melanie Jones and Cristina Sechel for providing helpful comments. We would also like to thank Cristina Sechel for her help with ArcGIS. The original data creators, depositors and funders bear no responsibility for the further analysis or interpretation of the data presented in this study.

Jennifer Roberts acknowledges support for this work from the Health Foundation, under their Social and Economic Value of Health programme, award no. 751630.

NOTES

1. Recently, Low and Pistaferri (2020) have reviewed the literature on disability insurance in the USA and the UK, and find that research has tended to overemphasize the extent of false claims, rather than considering how to improve insurance targeting to alleviate false rejection of genuine claimants. They find that the latter is the bigger problem, although most of their empirical evidence comes from the USA.
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 QLFS accessed via the UK Data Service).
4. Rates calculated from the claimant count and population estimates accessed via NOMIS (www.nomisweb.co.uk, accessed 29 May 2021), a service provided by the Office for National Statistics containing official labour market statistics.
5. Data from the Labour Force Survey accessed via NOMIS.
6. Data from the ASHE accessed via NOMIS. ASHE is an employer survey, and the geographical information refers to the local authority where the employer is located, rather than where the employee lives. Hence the wages are averaged over those working in an area.
7. Data from the 2011 Census accessed via NOMIS.
8. Data from DWP (2017b).
9. Berthoud (2004) calculates exit rates from disability benefit for 1999 to 2002 and finds that long-term claimants have low prospects of ever leaving Incapacity Benefit. This is supported by the qualitative work of Kemp and Davidson (2010).
10. See www.gov.uk/government/collections/benefit-expenditure-tables (accessed 29 May 2021).
11. While these benefits support those who are unable to work, there is evidence that they may contribute to low participation rates among people with disabilities (e.g. Autor and Duggan 2003; Jones and McVicar 2017). While these benefits support those who are unable to work, there is evidence that they may contribute to low participation rates among people with disabilities (e.g. Autor and Duggan 2003; Jones and McVicar 2017).

12. Anyadike-Danes (2010) also finds only limited evidence for regional convergence in disability claims over the period 2000 to 2007. Anyadike-Danes (2010) also finds only limited evidence for regional convergence in disability claims over the period 2000 to 2007.
13. Milligan and Schirle (2019) refer to the ‘push’ of weak labour markets and the ‘pull’ of more generous benefits.
14. Individuals can work (or be unemployed but deemed capable of work) and still claim PIP. However, work capability may reduce the amount of PIP to which individuals are entitled because this is interpreted as reflecting a greater degree of functioning, hence a lower level of disability. Individuals can work (or be unemployed but deemed capable of work) and still claim PIP. However, work capability may reduce the amount of PIP to which individuals are entitled because this is interpreted as reflecting a greater degree of functioning, hence a lower level of disability.
15. ESA itself is now being replaced by Universal Credit (UC), which will integrate six means-tested benefits, although the UC rollout has been subject to a number of delays. Between 2019 and 2024, the DWP is planning to move the majority of existing claimants to UC through managed migration. By 2021 (the time of writing), the date that claimants move from ESA to UC is determined by whether there has been a significant change in circumstances, such as failing a work capability assessment.
16. We now know that the claimant count fell by less than 300,000 over that period (Emmerson et al. 2017).
17. ESA claimants are placed in the *work-related activity group*, whose members are expected to prepare for eventual return to work (receiving a lower rate of ESA and attending regular interviews at the job centre), or the *support group*, whose members 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 group, which is much greater than planned (Emmerson et al. 2017).
18. In 2012, the OBR assumed that as the replacement of IB with ESA continued, the caseload would fall by 21% by 2015–16. However, it actually fell by only 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 1.6% in 2012 to 5% in 2018, while the proportion on IB falls from 4.8% to 0.4% over the same period. (Transitions between benefits over time are shown in Table 1.) In 2012, the OBR assumed that as the replacement of IB with ESA continued, the caseload would fall by 21% by 2015–16. However, it actually fell by only 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 1.6% in 2012 to 5% in 2018, while the proportion on IB falls from 4.8% to 0.4% over the same period. (Transitions between benefits over time are shown in Table 1.)
19. We allow for a gender-specific pension age, which varies according to year of birth. See https://assets.publishing.service.gov.uk/government/uploads/system/uploads/attachment_data/file/310231/spa-timetable.pdf (accessed 29 May 2021).
20. For covariates where there are missing values, we drop observations if the variable is time-varying. For missing values for time-invariant covariates, we impute from adjacent observations. Full details are given in the Table A1 of the Appendix.
21. There are 376 LADs in the UKHLS.
22. The small percentage (2.40%) 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. The small percentage (2.40%) 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.
23. We consider overlaps in benefit claims found in the UKHLS with data from the Family Resources Survey (FRS) where for the same period, comparable figures are revealed in the FRS: 27% claim both ESA/IB and PIP/DLA; 30% are ESA claimants only; and 36% claim PIP/DLA only.
24. We rely on self-reported benefit information. The literature has typically found that under-reporting is more likely than over-reporting, especially for IB; for example, see Lynn et al. (2012), which may bias our estimates downwards. To get a sense of the quality of our data, we compare the benefit claim rates in the UKHLS (by gender, by age and over time) to DWP administrative data (see Table A2 of the Appendix). The patterns are similar for both PIP/DLA and ESA/IB between the UKHLS and DWP data sources. Claimant rates generally increase within year by age, and trends over time are also consistent. We rely on self-reported benefit information. The literature has typically found that under-reporting is more likely than over-reporting, especially for IB; for example, see Lynn et al. (2012), which may bias our estimates downwards. To get a sense of the quality of our data, we compare the benefit claim rates in the UKHLS (by gender, by age and over time) to DWP administrative data (see Table A2 of the Appendix). The patterns are similar for both PIP/DLA and ESA/IB between the UKHLS and DWP data sources. Claimant rates generally increase within year by age, and trends over time are also consistent.
25. 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 on 25,855 individuals (N) and total observations of 87,840 (NT). 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 on 25,855 individuals (N) and total observations of 87,840 (NT).
26. We have also experimented with including the number of WCA repeat assessments carried out as proportion of the local claimant count (obtained from the DWP Stat-Xplore tool—<https://stat-xplore.dwp.gov.uk/webapi/jsf/login.xhtml>, accessed 29 May 2021) as an additional local labour market control. The repeat assessment rate reflects the stringency with which new procedures are being implemented locally. As expected, high WCA repeat assessment rates lower the likelihood of claiming ESA/IB, but the magnitude of the effect is small compared to unemployment. We exclude this variable from our main analysis due to concerns that it may be simply picking up the size of the existing IB stock, and furthermore it is likely to be endogenous.
 27. This is why we do not report specifications that decompose the number of health conditions into specific types. This is why we do not report specifications that decompose the number of health conditions into specific types.
 28. 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 4–7.
 29. Although the dependent variable for 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. Although the dependent variable for 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.
 30. A caveat with the system GMM analysis is that the predicted probability is not bound between 0 and 1. A caveat with the system GMM analysis is that the predicted probability is not bound between 0 and 1.
 31. See the notes for Table 9 for the source of the OBR forecast.
 32. Common characteristics throughout are based on the dominant binary categories from Table 2: female; white; non-immigrant; aged 45–54; one adult in the household (excluding respondent); dependent children aged 5–11; degree-level education; married; home owned on mortgage with equity; lives in an urban area; year of interview 2018. With the exception of the analysis shown in panel C of Table 9, the region of residence is London. When modelling unemployment scenarios (panels C and D of Table 9), we undertake the analysis for all three types of ADL health problem, i.e. mild, moderate and severe health states. The reason for this is that in panels C and D we are looking at the effect of unemployment changes on the probability of receiving ESA/IB benefits, where having health problems is a necessary but not sufficient condition for claiming (whereas in panels A and B we consider the onset of ADL problems). Common characteristics throughout are based on the dominant binary categories from Table 2: female; white; non-immigrant; aged 45–54; one adult in the household (excluding respondent); dependent children aged 5–11; degree-level education; married; home owned on mortgage with equity; lives in an urban area; year of interview 2018. With the exception of the analysis shown in panel C of Table 9, the region of residence is London. When modelling unemployment scenarios (panels C and D of Table 9), we undertake the analysis for all three types of ADL health problem, i.e. mild, moderate and severe health states. The reason for this is that in panels C and D we are looking at the effect of unemployment changes on the probability of receiving ESA/IB benefits, where having health problems is a necessary but not sufficient condition for claiming (whereas in panels A and B we consider the onset of ADL problems).
 33. Based on the dominant category of female and aged 45–54, where the number claiming ESA/IB in 2018 was 312,900 (figures from Stat-Xplore—see above), which as proportion of the total number of claimants in 2018 was 14.5%.
 34. The analysis in panel D of Table 9 is based on common characteristics except LAD unemployment rates, where are all increased by the same proportion as indicated under the OBR forecast.

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APPENDIX

TABLE A1
SAMPLE DERIVATION

Step	Description	
1	After appending waves 1–9 of the UKHLS, start with sample size of N individuals (NT observations)	$N = 85,837$ ($NT = 407,189$)
2	Drop individuals who move house	$N = 82,249$ ($NT = 376,735$)
3	Drop individuals aged below 16	$N = 82,211$ ($NT = 376,671$)
4	Drop full-time students, those looking after family, retired, on maternity leave, on government training scheme, self-employed	$N = 55,339$ ($NT = 208,119$)
5	Drop Northern Ireland	$N = 52,014$ ($NT = 194,800$)
6	Drop if individual aged greater than gender and year-of-birth-specific state pension age	$N = 50,156$ ($NT = 188,321$)
7	Drop any individual on Universal Credit	$N = 50,092$ ($NT = 187,576$)
8	Drop any unmatched observations after merging in LAD specific covariates	$N = 46,542$ ($NT = 172,829$)
9	Drop any observations where unemployment rate or replacement ratio is missing	$N = 46,149$ ($NT = 167,339$)
10	Drop first observation in which individual is observed, as this is used for constructing initial values of benefit state	$N = 33,350$ ($NT = 121,190$)

TABLE A2
 BENEFIT CLAIM RATES BY GENDER, AGE AND OVER TIME FOR GREAT BRITAIN—DWP
 (UKHLS) PERCENTAGES

	2010	2011	2012	2013	2014	2015	2016	2017	2018
<i>% PIP/</i>									
<i>DLA</i>									
<i>Males</i>									
Aged 16–	3.46	3.58	3.74	3.85	4.16	4.38	4.37	4.36	4.36
24	(2.61)	(2.35)	(2.41)	(2.92)	(2.09)	(1.52)	(2.93)	(3.73)	(4.34)
Aged 25–	2.75	2.80	2.92	2.92	3.06	3.29	3.36	3.37	3.40
34	(2.49)	(1.77)	(2.12)	(1.86)	(2.14)	(2.66)	(2.82)	(3.29)	(5.41)
Aged 35–	4.02	4.00	4.01	3.89	3.97	4.17	4.14	4.06	4.02
44	(3.19)	(3.34)	(3.03)	(2.92)	(3.15)	(3.49)	(5.75)	(3.83)	(2.78)
Aged 45–	5.88	5.86	5.85	5.74	5.91	6.26	6.26	6.14	6.06
54	(4.92)	(5.35)	(5.56)	(4.99)	(4.56)	(4.62)	(4.88)	(4.55)	(4.61)
Aged 55–	9.39	9.15	9.05	8.73	8.90	9.37	9.41	9.26	9.08
65	(8.18)	(7.62)	(6.96)	(7.51)	(6.45)	(7.72)	(8.36)	(8.75)	(9.69)
Total 16–	5.01	4.99	5.02	4.94	5.11	5.41	5.43	5.38	5.34
65	(4.28)	(4.39)	(4.27)	(4.17)	(3.93)	(4.33)	(4.56)	(5.01)	(5.35)
<i>% PIP/</i>									
<i>DLA</i>									
<i>Females</i>									
Aged 16–	2.13	2.17	2.25	2.25	2.41	2.57	2.59	2.63	2.68
24	(1.75)	(1.80)	(0.96)	(1.11)	(1.33)	(2.35)	(1.94)	(2.69)	(2.52)
Aged 25–	2.43	2.47	2.54	2.52	2.66	2.92	3.00	3.04	3.10
34	(2.50)	(2.31)	(3.19)	(2.96)	(2.88)	(3.43)	(4.69)	(4.00)	(3.19)
Aged 35–	4.23	4.20	4.19	4.05	4.23	4.53	4.53	4.51	4.51
44	(5.11)	(4.54)	(4.44)	(4.57)	(5.09)	(5.47)	(2.89)	(5.82)	(6.45)
Aged 45–	4.48	4.45	4.45	4.38	4.59	4.96	5.03	5.02	5.02
54	(6.74)	(6.37)	(7.00)	(6.02)	(6.21)	(6.59)	(7.22)	(7.63)	(7.64)
Aged 55–	10.73	10.50	10.42	10.15	10.42	11.06	11.22	11.19	11.10
65	(12.50)	(9.35)	(9.21)	(9.01)	(9.70)	(9.87)	(10.95)	(10.37)	(13.74)
Total 16–	4.71	4.66	4.66	4.56	4.76	5.12	5.21	5.24	5.27
65	(5.72)	(5.26)	(5.52)	(5.23)	(5.56)	(6.07)	(6.73)	(6.81)	(7.52)
<i>% ESA/</i>									
<i>IB</i>									
<i>Males</i>									
Aged 16–	2.37	2.33	2.36	2.54	2.86	2.87	2.79	2.53	1.97
24	(3.11)	(2.17)	(2.13)	(2.12)	(2.22)	(2.88)	(2.37)	(2.88)	(2.35)
Aged 25–	4.69	4.55	4.44	4.49	4.80	4.73	4.60	4.28	3.74
34	(3.27)	(2.53)	(2.69)	(2.67)	(2.98)	(3.76)	(3.81)	(3.37)	(3.96)
Aged 35–	7.10	6.94	6.62	6.42	6.52	6.28	5.95	5.47	4.78
44	(7.69)	(2.49)	(2.59)	(3.10)	(2.61)	(3.60)	(3.43)	(3.39)	(2.91)
Aged 45–	9.38	9.21	8.82	8.57	8.59	8.36	8.01	7.50	6.82
54	(5.27)	(6.33)	(6.58)	(4.86)	(5.19)	(4.26)	(4.83)	(4.75)	(5.15)
Aged 55–	14.14	13.44	12.57	11.61	11.15	10.76	10.39	10.05	9.40
65	(17.27)	(9.02)	(7.77)	(7.27)	(6.87)	(7.32)	(7.28)	(6.67)	(7.75)
Total 16–	7.47	7.24	6.90	6.68	6.75	6.58	6.34	5.98	5.37
65	(7.32)	(4.82)	(4.67)	(4.22)	(4.23)	(4.49)	(4.84)	(4.76)	(4.88)

TABLE A2
CONTINUED

	2010	2011	2012	2013	2014	2015	2016	2017	2018
<i>% ESA/ IB</i>									
<i>Females</i>									
Aged 16–	1.92	1.88	1.89	2.02	2.29	2.30	2.26	2.06	1.60
24	(2.81)	(2.40)	(2.89)	(1.90)	(2.51)	(3.34)	(2.75)	(2.85)	(2.36)
Aged 25–	3.49	3.54	3.57	3.60	3.85	3.84	3.79	3.59	3.17
34	(2.90)	(2.05)	(2.21)	(2.19)	(2.75)	(3.95)	(4.12)	(3.15)	(3.19)
Aged 35–	5.82	5.86	5.71	5.56	5.66	5.47	5.22	4.87	4.38
44	(3.78)	(3.07)	(3.35)	(3.27)	(3.89)	(3.94)	(4.40)	(4.67)	(4.49)
Aged 45–	6.05	5.97	5.74	5.56	5.58	5.46	5.28	5.02	4.64
54	(5.44)	(5.22)	(5.32)	(4.98)	(5.18)	(5.77)	(5.93)	(5.79)	(5.64)
Aged 55–	6.98	7.52	7.95	8.23	8.66	9.04	9.43	9.85	10.01
65	(8.64)	(7.98)	(9.07)	(8.44)	(8.15)	(8.99)	(8.58)	(7.91)	(11.13)
Total 16–	5.02	5.10	5.07	5.06	5.25	5.25	5.21	5.09	4.79
65	(4.71)	(4.24)	(4.62)	(4.37)	(4.72)	(5.42)	(5.50)	(5.38)	(5.93)

Notes

Figures in parentheses are based on the UKHLS estimation sample. Other figures are based on data from DWP obtained from NOMIS and Stat-Xplore, an online tool from the DWP (<https://stat-xplore.dwp.gov.uk/webapi/jsf/login.xhtml>, accessed 29 May 2021).