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Abstract

There is a gap between the employment rates of disabled and non-disabled people in the UK, which stood at 33 percentage points in 2019. This Disability Employment Gap (DEG) is a cause for concern in government and among anyone worried about poverty and disadvantage. We aim to better understand the DEG by decomposing it into its constituent parts and constructing counterfactual scenarios to demonstrate how it would change if inequalities in education were eliminated or structural barriers to employment were removed. Our results show that if the average education levels of disabled people could be raised to those of non-disabled people, without changing other characteristics or structural barriers in the labour market, then the DEG could be reduced by just 4pp (12%). However, if structural barriers could be eliminated such that a disabled person with a given level of education has the same probability of employment as a non-disabled person with the same level of education, then the DEG could be reduced by over 28pp (85%), a quarter of which would be achieved through eliminating barriers faced by people with no formal qualifications. These findings challenge the notion that tackling supply side issues alone would substantially reduce the DEG and highlight the continued relevance of barriers in the labour market that are disproportionately hindering the employment prospects of disabled people.

Keywords: disability employment gap, decomposition, education

JEL classification: I14, J24, J71

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1. Introduction

In 2019 the overall employment rate for disabled people aged between 25 and 64 in the UK was 53%, compared to 86% for non-disabled people, leading to a disability employment gap (DEG) of 33 percentage points (pp). The gap is even more stark for disabled people with a mental health condition; this group had an employment rate of only 40% in 2019.[5] These gaps are not unique to the UK; there is a sizable gap in employment rates between disabled and non-disabled people in all OECD countries (MacDonald et al., 2020).

While work is not appropriate for all disabled people, there are a number of reasons why the size of the DEG should be a cause for concern. Many disabled people currently not in work say that they want to work, and good work can also help people flourish in a more holistic sense through improved health and wellbeing. Work is also key to poverty reduction, and persistent worklessness among certain groups is an underlying cause of inequality and reduced opportunities. In the working age population, the poverty rate among disabled people is more than twice that for non-disabled people, at 38% compared to 17% (Joseph Rowntree Foundation, 2022). Moreover, higher employment rates lead to increased economic output and tax revenue. Getting more disabled people into work has long been an aim of UK government policy (Department for Work and Pensions/ Department of Health, 2017) and a better understanding of the underlying causes of the current employment gaps can contribute to these policy goals, as well as the longer-term flourishing of disabled people.

Disability is a protected characteristic under the Equality Act (2010) and, as such, employers must not discriminate against disabled people with respect to offering employment, terms of employment, access to promotion or any other benefit, or dismissal. The Act also places a duty on employers to make reasonable adjustments to limit any disadvantage that a disabled person might experience in the workplace. The DEG is much wider than similar employment gaps pertaining to other protected characteristics. For example, the gender and ethnicity employment gaps were estimated to be 8pp and 11pp respectively in 2019.[6]

The gap in employment rates between disabled people and non-disabled people reflects the relative supply of workers (characteristics of the pool of available labour) and demand (number and nature of available jobs). In turn a number of interrelated factors underlie supply and demand. Disabled people’s labour supply may be affected by welfare policies, household

[5] All figures are the authors’ own calculations from the Annual Population Survey.
[6] Ibid.

structure and local area characteristics such as availability of transport and health provision. Meanwhile demand is affected by employer behaviour (including a willingness to make workplace accommodations), the state of the local economy and broader societal attitudes to disability.

In this paper, we develop a model that captures many of these influences, and we isolate the effects of one particularly important supply side factor: the role that education plays in the DEG, and the extent to which a lack of qualifications presents a barrier to disabled people accessing employment. We focus on education because of the important link between human capital accumulation and labour market outcomes, and because it has been neglected in the existing literature on disability and employment. While most empirical studies focused on disability wage gaps or employment gaps include educational attainment as a control variable (see for example Baldwin and Johnson, 2000; Berthoud, 2008; Jones and McVicar, 2020), it is rarely the focus of study and there is very little evidence for the UK on the contribution that education makes to disabled people's employment prospects, and how this compares to that for non-disabled people.[7] Education is also a factor that is potentially modifiable by policy, hence it could be an important tool to narrow the DEG.

It is well known that there are substantial returns to education, in terms of higher expected earnings. People with lower levels of education therefore have less incentive to participate in the labour market, as ceteris paribus the marginal benefit of doing so is smaller. In other words, where the expected wage is no greater than the reservation wage (perhaps determined by the availability of out-of-work benefits), one is unlikely to choose to participate (Kidd et al., 2000). Moreover, less educated people choosing to participate are more likely to experience unemployment than more educated workers (Mincer, 1991). As a result, we would expect employment rates to be higher among those with higher level qualifications.

If disabled people have lower levels of education on average than non-disabled people, then for this reason alone we would expect them to have lower employment rates. There is evidence that the onset of disability in childhood or adolescence gives rise to significant barriers to educational attainment (Athanasou et al., 2019; Mann and Honeycutt, 2014). Moreover, there is a significant link between socioeconomic outcomes and disability onset in later life (Latham, 2012) such that people with low levels of education are more likely to become disabled in working age.

[7] In one valuable contribution Jones and Sloane (2010) explore disability and skill mismatch. They do not tackle the role of education head-on, but they find that disabled people are more likely to be skill mismatched in the UK labour market, and allow that this could be due to over- or under-education.

This gives rise to our first research question. If this educational divide were to be eliminated entirely, then by how much would the DEG be reduced?

Having eliminated (hypothetically) all inequalities in educational attainment, any remaining DEG is due to disabled people experiencing lower employment rates despite having the same qualification levels. This may be due to differences in other observed individual or household characteristics that affect labour supply, but it may also imply the existence of structural barriers to disabled people's employment. The underlying reasons for these structural barriers are subject to much debate in the literature. Lower employment levels could be due to latent productivity differences, possibly but not necessarily directly related to health conditions, which are not reflected in formal qualifications. There is a debate in disability studies about how to conceptualise the impacts of health on work performance (Jones and Wass, 2013). In the 'medical' model, a person's health impairment directly reduces their ability to function in society, including in the labour market. On the other hand, according to the 'social' model, reduced functioning arises because social institutions and practices are not adapted to the needs of people with health impairments. Thus, people with impairments are disabled by social structures, not their underlying condition. The social model has been criticised for downplaying the role of impairments as well as individual differences in how they are experienced (Shakespeare, 2017). An alternative 'biopsychosocial' model combines elements of the medical and social models, and stresses that what counts is an impaired person's fit to a given environment (Chandola and Rouxel, 2021; World Health Organisation, 2001). In economic terms, these models differ on whether the impact of health conditions on employment operates via supply (the medical model), demand (the social model) or both (the biopsychosocial model). We take the latter position in this paper, recognising the particular status of disability in culture and legislation (it is not simply a health impairment), but also differences in how institutions affect individuals.

Many structural barriers are manifested in the workplace, for instance in the way jobs are designed or what equipment is provided. Some barriers may be inherent to the job (for example, very physically demanding roles), but others can be overcome by workplace adjustments (for example, special equipment or flexible working arrangements). Discrimination occurs when employers fail in their legal duties to offer reasonable adjustments (that is adjustments that are practical and affordable). Similarly, employers may also discriminate by disproportionately passing over suitably skilled disabled people for employment opportunities.

The DEG may also be influenced by systematic differences between disabled and non-disabled people in their preference for work, leading to disabled people being less willing to seek work. This may be linked to inherent capacities (the medical model) but also social structures (the social and biopsychosocial models). The existence of these structural barriers is likely to discourage disabled people from participating in the labour market in the first place. This leads to longer periods out of work which in turn reduces the (actual or perceived) value of people's skills and experience, making them less employable (Kroft et al., 2013). As such, it is difficult to dissociate preferences from broader structural factors (although we attempt to do so in part of our analysis using stated preference data and information on attachment to the labour market).

Our consideration of structural factors motivates our second research question. How do these structural gaps in employment vary across different qualification levels, and at what point in the qualifications hierarchy are the main effects seen? For example, does the main explanatory power come from the lower end of the human capital distribution, contrasting people who do and do not have any formal educational qualifications; or it is more informative to consider the different prevalence of higher education among disabled and non-disabled people?

These research questions are addressed by applying decomposition methods to the Annual Population Survey (APS). We decompose the DEG into two main parts: the part that can be explained by differences in education and other characteristics between disabled and non-disabled people; and the remaining part which we attribute to differences in the employment structure, causing disabled people to be employed at different rates to non-disabled people with the same levels of education and other characteristics. Extending this analysis, we use the results to construct counterfactual scenarios to demonstrate how the DEG would change if inequalities in education were eliminated or structural barriers to employment were removed. Further, by employing a novel application of the approach proposed by Fortin et al. (2011) our analysis provides insights into how these barriers vary across different levels of education.

This paper makes three important contributions to knowledge of disability and employment. Firstly, while decomposition techniques have been applied to the DEG in previous studies, far too little attention has been paid to how to decompose the gap, and importantly how to interpret the results. Typically, the standard Oaxaca-Blinder decomposition (Oaxaca, 1973; Blinder, 1973) is used unquestioningly, despite a number of developments in the methods literature which show that there are many valid (non-unique) ways to decompose an outcome gap, and that different methods imply different interpretations. We exploit these methodological developments in order to implement solutions to the ‘index problem’ and the ‘omitted category problem’, allowing us to select the most appropriate decomposition to answer our specific research questions. Further, we stress that different methods imply potentially very different policy relevance, and we illustrate this by constructing meaningful counterfactual scenarios. Secondly, and in contrast to previous literature, we acknowledge that there is not just one relevant DEG. Instead, we consider different gaps defined according to sex, age, type of health condition, severity of impairment, people’s preference for paid work and their relative attachment to the labour market; these latter two factors in particular are largely neglected in the existing literature. We show that the role of education differs according to which gaps we consider. Our final contribution is to provide up-to-date evidence on the role that education can play in narrowing the DEG in the UK.

Our results show that a relatively small proportion of the DEG can be explained by disabled people having a lower level of education than non-disabled people. If parity of education could be achieved without any accompanying change to the employment structure, we predict that this would reduce the DEG by just over four percentage points. Meanwhile, in a hypothetical scenario where all structural barriers are eliminated such that disabled people have the same access to employment without changing their level of education and other characteristics, the DEG would reduce by over 28 percentage points. A quarter of this impact (seven percentage points) could be achieved by focusing only on the barriers that affect people with no qualifications. This is due to the fact that both a large number of disabled people have no qualifications and the DEG is particularly high among this group. These results imply that, while helping disabled people to access higher qualifications will improve their employment rate, a far greater impact could be achieved through addressing structural barriers in the labour market that cause disabled people to be employed at a lower rate than similarly skilled non-disabled people.

2. Literature

This paper builds on previous research using decomposition methods to explore the DEG and disability gaps in other labour market outcomes. Kidd et al. (2000) estimate that productivity related characteristics can explain about half of both the labour force participation gap and the wage gap in the UK; for wages they find education qualifications and experience explain less of the gap than occupation and industry. Thoursie (2004) decomposes disability gaps in Sweden relating to wages and occupational distribution and finds that educational qualifications explain a substantial part of the gap. The lower wages earned by disabled people are primarily explained by disabled people being less qualified on average for higher level occupations. Jones (2006) finds that 75% of the DEG in the UK is unexplained by characteristics. However, she concludes that this ‘unexplained’ gap is wholly due to productivity differences between disabled and non-disabled people because there is no DEG when only non-work limited disabled people are included in the analysis. A similar conclusion is reached by Longhi et al. (2012), in relation to the disability wage gap in the UK, insofar as productivity differences alone account for the wage gap and there is little evidence of discrimination. It is worth noting here that a lack of discrimination amongst similarly productive workers does not imply there are no structural barriers to employment. As we discuss above, productivity differences may themselves be the result of structural factors.

Baldwin and Marcus (2007) decompose the DEG and disability wage gaps in the US among people with mental health conditions. They find that 80% of the gap can be explained by the characteristics in the model, but this is mainly due to the fact that health status, measured via functional limitations, physical health problems and substance use problems, is included as a characteristic. Mitra and Kruse (2016), also using US data, specifically look at the disability gap in job loss. Here, everyone in the sample is initially employed and hence the authors are able to include employment-specific characteristics, such as industry and occupation in their model. Nevertheless, their decomposition explains a very small share (3%) of the gap in job loss for women and a negative share (-5%) for men; indicating that if disabled men had the same characteristics as non-disabled men, the gap in job loss would be even larger.

Focusing on education, several papers explore the interactive effects of disability and education on labour market outcomes, with studies consistently finding that higher levels of education mitigate the disadvantages experienced by disabled people, while these disadvantages are exacerbated by low levels of education. These findings are consistent across several countries including Australia (Werth, 2012; Polidano and Vu, 2015), Denmark (Heinesen and Kolodziejczyk, 2013), Italy (Agovino and Parodi, 2014; Addabbo and Sarti, 2016), Sweden (Andren, 2008; Lundborg et al., 2015), the UK (Banks et al., 2015; Jones and McVicar, 2020) and the US (Sevak et al., 2015; Venti and Wise, 2015; McCauley, 2020). However, while education helps disabled people to find and remain in employment, there is also evidence to suggest that many disabled people are overqualified for the work that they do. Jones et al. (2014) find that becoming work-limited disabled increases the probability of becoming overeducated but has no effect on becoming over-skilled. This is consistent with the notion that disability onset is associated with downward occupational movements. Also, the effect of education on the labour market outcomes of disabled people is related to the timing of disability onset. Hollenbeck and Kimmel (2008) find that males who become disabled later in life, having already completed their education, experience better returns to education than males who become disabled at a younger age. This seems to contrast with the findings of Wilkins (2004), where males experiencing the onset of disability before completing their education experience better labour market outcomes. Henderson et al. (2017) show that there is significant heterogeneity in the returns to education for disabled people.

3. Method

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

$$y_i^D = \beta_0^D + \mathbf{q}_i^D \boldsymbol{\beta}_q^D + \mathbf{x}_i^D \boldsymbol{\beta}_x^D + \varepsilon_i^D \tag{1}$$

For each individual i, $y_i \in (0,1)$ denotes whether they are in employment. Every individual holds one of 11 educational levels as their highest qualification (see Table A1). This is denoted by the vector $\mathbf{q}_i^D = (q_{i1}^D, \ldots, q_{i11}^D)$where $q_{ik}^D \in (0,1)$ and $\sum_{k=1}^{11} q_{ik}^D = 1$. The vector $\boldsymbol{\beta}_q^D$ contains the coefficients pertaining to each qualification. Following Jann (2008), these coefficients are normalised to avoid arbitrarily choosing a baseline qualification level, and we discuss this further below. All other personal and household characteristics, including a set of dummy variables denoting the local authority of residence, are incorporated in the vector $\mathbf{x}_i^D$. An important distinction between $\mathbf{q}_i^D$ and $\mathbf{x}_i^D$ is that while $\mathbf{q}_i^D$ (education) is a potentially modifiable target for policy, the components of $\mathbf{x}_i^D$ are either non-modifiable, such as age, gender and ethnicity, or are not usually the objects of policy intervention, such as those relating to household structure and housing tenure. Our focus in the decompositions is on the contribution of $\mathbf{q}_i^D$ and its related structural barriers to the DEG.

Estimating equation (1) by Ordinary Least Squares (OLS), the overall employment rate by disability status can be expressed as follows.

$$\bar{y}^D = \hat{\beta}_0^D + \bar{\mathbf{q}}^D \widehat{\boldsymbol{\beta}}_q^D + \bar{\mathbf{x}}^D \widehat{\boldsymbol{\beta}}_x^D \tag{2}$$

Subtracting the equation for disabled people from the non-disabled equation gives the DEG:

$$\bar{y}^0 - \bar{y}^1 = \left(\hat{\beta}_0^0 - \hat{\beta}_0^1\right) + \left(\bar{\mathbf{q}}^0 \widehat{\boldsymbol{\beta}}_q^0 - \bar{\mathbf{q}}^1 \widehat{\boldsymbol{\beta}}_q^1\right) + (\bar{\mathbf{x}}^0 \widehat{\boldsymbol{\beta}}_x^0 - \bar{\mathbf{x}}^1 \widehat{\boldsymbol{\beta}}_x^1) \tag{3}$$

Following Oaxaca (1973) and Blinder (1973), equation (3) can be expressed as a decomposition of the DEG into the sum of its parts.

$$\bar{y}^0 - \bar{y}^1 = (\bar{\mathbf{q}}^0 - \bar{\mathbf{q}}^1)\widehat{\boldsymbol{\beta}}_q^0 + (\bar{\mathbf{x}}^0 - \bar{\mathbf{x}}^1)\widehat{\boldsymbol{\beta}}_x^0 + \left(\hat{\beta}_0^0 - \hat{\beta}_0^1\right) + \bar{\mathbf{q}}^1\left(\widehat{\boldsymbol{\beta}}_q^0 - \widehat{\boldsymbol{\beta}}_q^1\right) + \bar{\mathbf{x}}^1\left(\widehat{\boldsymbol{\beta}}_x^0 - \widehat{\boldsymbol{\beta}}_x^1\right) \qquad (4)$$

The first term on the right-hand side of equation (4) identifies the part of the DEG attributable to differences in the education levels of disabled and non-disabled people. The second term identifies the part attributable to differences between disabled and non-disabled people in other observable characteristics. The third, fourth and fifth terms together identify the structural component of the DEG, which quantifies the size of the DEG if there were no differences in education levels or other observable characteristics. This latter component may incorporate differences in unobservable characteristics between the two groups but also reflects the extent to which disabled people and non-disabled people are treated differently or behave differently in their interactions with the labour market despite having the same characteristics.

One way to interpret the arrangement of equation (4) is to assume that, in a world with no structural barriers, the non-disabled coefficients in equation (2) ($\hat{\beta}_0^0$, $\widehat{\boldsymbol{\beta}}_q^0$ and $\widehat{\boldsymbol{\beta}}_x^0$) would represent the employment structure of both groups (so $\hat{\beta}_0^1 = \hat{\beta}_0^0$, $\widehat{\boldsymbol{\beta}}_q^1 = \widehat{\boldsymbol{\beta}}_q^0$ and $\widehat{\boldsymbol{\beta}}_x^1 = \widehat{\boldsymbol{\beta}}_x^0$). In this counterfactual world, the last three terms of the equation would be zero and the only remaining DEG would be due to differences in education and other characteristics, valued according to the counterfactual employment structure. The structural component (the last three terms) is the difference between this counterfactual DEG and the actual DEG. While this seems a plausible interpretation, Oaxaca (1973) shows that the gap can just as well be decomposed such that the disabled coefficients represent the counterfactual employment structure, as in equation (5).

$$\bar{y}^0 - \bar{y}^1 = (\bar{\mathbf{q}}^0 - \bar{\mathbf{q}}^1)\widehat{\boldsymbol{\beta}}_q^1 + (\bar{\mathbf{x}}^0 - \bar{\mathbf{x}}^1)\widehat{\boldsymbol{\beta}}_x^1 + \left(\hat{\beta}_0^0 - \hat{\beta}_0^1\right) + \bar{\mathbf{q}}^0\left(\widehat{\boldsymbol{\beta}}_q^0 - \widehat{\boldsymbol{\beta}}_q^1\right) + \bar{\mathbf{x}}^0\left(\widehat{\boldsymbol{\beta}}_x^0 - \widehat{\boldsymbol{\beta}}_x^1\right) \qquad (5)$$

Whether equation (4) or (5) is the most pertinent for our purposes depends on the policy question of interest (Jones and Kelley, 1984). Equation (4) implicitly assumes the goal is to remove the barriers faced by disabled people relative to non-disabled people. In contrast, equation (5) assumes a counterfactual world in which policy seeks to remove the unfair advantage of non-disabled people by exposing them to the same barriers as disabled people. It seems reasonable to assume that the goal of policy is to remove barriers not add to them, suggesting that equation (4) is the appropriate formulation to explore the effects of a policy to address structural barriers.

On the other hand, a policy objective of reducing educational inequalities could be achieved by either reducing the qualification levels of non-disabled people to that of disabled people, as implied by the first term of equation (4), or raising the qualification levels of disabled people to that of non-disabled people as implied by the first term of equation (5). In this case, it makes more sense to model the effects of the latter option so equation (5) represents the more useful decomposition. If sufficient investment in education were made such that disabled people had the same qualification levels on average as non-disabled people, then the first term in equation (5) would be zero and the remaining DEG would be attributable to a further characteristics component (the second term) plus the structural component (third, fourth and fifth terms).

Equations (4) and (5) can also be used to show the effects of secondary policy changes. Having eliminated all inequalities in employment structure such that $\hat{\beta}_0^1 = \hat{\beta}_0^0$, $\widehat{\boldsymbol{\beta}}_q^1 = \widehat{\boldsymbol{\beta}}_q^0$ and $\widehat{\boldsymbol{\beta}}_x^1 = \widehat{\boldsymbol{\beta}}_x^0$, the first term in equation (4) could subsequently be reduced by a further policy intervention that seeks to improve the educational attainment of disabled people. Similarly, equation (5) implies that, having eliminated educational inequalities such that $\overline{\mathbf{q}}^1 = \overline{\mathbf{q}}^0$, the structural component could subsequently be reduced by a further policy intervention that seeks to address the employment structure (i.e. the factors leading to disabled people having lower employment rates despite having similar qualifications). Note that policy interventions are unlikely to affect the second term of either equation, on the assumption that (unlike education) other characteristics affecting employability are generally non-modifiable.

Since both equations (4) and (5) can be usefully interpreted, in our analysis we report and discuss results for both. However, it should be noted that there are numerous other ways in which the DEG could be decomposed, including using a counterfactual employment structure that lies between $\widehat{\boldsymbol{\beta}}_q^1$ and $\widehat{\boldsymbol{\beta}}_q^0$.[8] Therefore, our results can be seen as bounds on a set of possible decompositions. The results of some other plausible decompositions are shown in Table A2.

Further methodological issues arise when breaking down the components of equations (4) and (5); these relate to the choice of omitted category out of a set of dummies based on a categorical variable (in our case, the highest educational qualification). The first issue applies to the component due to differences in education (first term in equations (4) and (5)), and by extension the component due to differences in other characteristics (second term). While the total size of the education component does not depend on the omitted qualification, a detailed decomposition of the contributions of individual qualifications is sensitive to this choice. There is no complete solution to this problem because the choice of omitted category can almost always be seen as arbitrary (Fortin et al., 2011). Furthermore, we also wish to quantify the

[8] This is the familiar index problem. See Jann (2008) for an explanation of the various decomposition options.

relative effects of all 11 qualifications that we consider in our analysis, rather than omitting a comparator qualification. Therefore, our strategy is to normalise the education coefficients, which amounts to taking the average of the detailed decompositions across all possible choices of omitted qualification.[9]

The second (and arguably more fundamental) methodological issue applies to any attempt to break down the structural component into its constituent parts: the part attributable to the difference in constants (third term); the part attributable to differences in the returns to education (fourth term); and the part attributable to differences in the returns to other characteristics (fifth term). Even the total size of the education part is sensitive to the choice of omitted qualification, as is the detailed decomposition of the differences in returns associated with individual qualifications.[10] There is no solution to this more severe problem. Instead, we adopt an approach initially proposed by Horrace and Oaxaca (2001) and subsequently applied to decompositions by Fortin et al. (2011). Given that $\sum_{k=1}^{11} \bar{q}_k^1 = 1$ where $\bar{q}_k^1$, $\hat{\beta}_{q_k}^0$ and $\hat{\beta}_{q_k}^1$ are the kth terms in $\bar{\mathbf{q}}^1$, $\widehat{\boldsymbol{\beta}}_q^0$ and $\widehat{\boldsymbol{\beta}}_q^1$ respectively, the structural component in equation (4) can be expressed as:

$$\Delta_{q^1}^s = \left(\hat{\beta}_0^0 - \hat{\beta}_0^1\right) + \bar{\mathbf{q}}^1\left(\widehat{\boldsymbol{\beta}}_q^0 - \widehat{\boldsymbol{\beta}}_q^1\right) + \bar{\mathbf{x}}^1\left(\widehat{\boldsymbol{\beta}}_x^0 - \widehat{\boldsymbol{\beta}}_x^1\right) = \sum_{k=1}^{11} \bar{q}_k^1 \, \Delta_{q_k^1}^s \qquad (6)$$

where

$$\Delta_{q_k^1}^s = \left(\hat{\beta}_0^0 - \hat{\beta}_0^1\right) + (\hat{\beta}_{q_k}^0 - \hat{\beta}_{q_k}^1) + \bar{\mathbf{x}}^1\left(\widehat{\boldsymbol{\beta}}_x^0 - \widehat{\boldsymbol{\beta}}_x^1\right) \qquad (7)$$

The term $\Delta_{q_k^1}^s$ in equation (6) is the DEG due to structural factors that is observed for individuals holding a highest qualification k, and with other characteristics fixed at their sample means for disabled people. It is made up of three parts: the differences in constants (the first term on the right-hand side of equation (7)); the differences in returns to qualification k (second term); and the effects due to differences in returns to other characteristics (third term). The structural

[9] Highest qualification is a categorical variable; thus we would usually expect one of the coefficients in $\boldsymbol{\beta}_q$ to be zero (the omitted category). Following Jann (2008), we normalise the highest qualification variable such that $\beta_{q_k} = \beta'_{q_k} - \frac{1}{11}\sum_{k=1}^{11} \beta'_{q_k}$ where β_{q_k} is the coefficient pertaining to the kth qualification in the normalised transformation and β'_{q_k} is the coefficient pertaining to the kth qualification, where one of the qualifications (it does not matter which) is omitted. It can be shown that $\sum_{k=1}^{11} \beta_{q_k} = 0$. The normalised coefficient β_{q_k} can be interpreted as the amount by which the dependent variable (probability of employment) would change if a typical individual moved from an 'average' qualification level to qualification level k. All categorical (non-binary) variables in $\mathbf{x}$ are also normalised.

[10] This problem is not solved by normalisation as this is just one of many transformations that all produce different estimates of $\bar{\mathbf{q}}^1\left(\widehat{\boldsymbol{\beta}}_q^0 - \widehat{\boldsymbol{\beta}}_q^1\right)$.

component of the overall DEG $\Delta^s_{q^1}$ is equal to the sum of the qualification-specific structural DEGs, weighted by the proportion of disabled people with each qualification as their highest, $\bar{q}^1_k$. Hence the share of the structural component attributable to qualification k can be expressed as the kth term of the summation in equation (6).

It is essential to interpret these shares correctly. The statistic $\Delta^s_{q^1_k}$ tells us by how much the DEG would reduce if all structural barriers were removed for everyone holding qualification k as their highest, not just those barriers specific to k (the second term on the right-hand side of equation (7)). This is because $\Delta^s_{q^1_k}$ essentially incorporates all other structural barriers affecting the employment of disabled people indicated by the constant $\left(\hat{\beta}^0_0 - \hat{\beta}^1_0\right) + \bar{\mathbf{x}}^1\left(\hat{\boldsymbol{\beta}}^0_x - \hat{\boldsymbol{\beta}}^1_x\right)$. As such, this statistic does not tell us the absolute contribution of individual qualifications to the overall structural component but does tell us the relative importance of different qualifications to the overall employment structure. As shown by Horrace and Oaxaca (2001) and Fortin et al. (2011), these relative contributions are invariant to the choice of omitted category, whereas the absolute contributions are not. Analogously, the structural component of equation (5) can be re-expressed as:[11]

$$\Delta^s_{q^0} = \left(\hat{\beta}^0_0 - \hat{\beta}^1_0\right) + \bar{\mathbf{q}}^0\left(\hat{\boldsymbol{\beta}}^0_q - \hat{\boldsymbol{\beta}}^1_q\right) + \bar{\mathbf{x}}^0\left(\hat{\boldsymbol{\beta}}^0_x - \hat{\boldsymbol{\beta}}^1_x\right) = \sum_{k=1}^{11} \bar{q}^0_k \Delta^s_{q^0_k} \tag{8}$$

where

$$\Delta^s_{q^0_k} = \left(\hat{\beta}^0_0 - \hat{\beta}^1_0\right) + \left(\hat{\beta}^0_{q_k} - \hat{\beta}^1_{q_k}\right) + \bar{\mathbf{x}}^0\left(\hat{\boldsymbol{\beta}}^0_x - \hat{\boldsymbol{\beta}}^1_x\right) \tag{9}$$

For comparison, we also show the breakdown of the structural component in the standard way (equations (4) and (5)) in Table A3 in the appendix. This table shows how the results and interpretation are very sensitive to the omitted category (or normalised specification).

4. Data

Our data source is the Annual Population Survey (APS). In order to access a comprehensive set of variables (including detailed information about health conditions), we use the Secure Access version of the APS (Office for National Statistics, 2022).[12] This is a cross-sectional

[11] To find estimates and standard errors for $\Delta^s_{q^1_k}$, $\Delta^s_{q^0_k}$, $\bar{q}^1_k\Delta^s_{q^1_k}$ and $\bar{q}^0_k\Delta^s_{q^0_k}$ for all k, we bootstrapped the employment regressions and equations (6)-(9) using 1,000 replications in Stata.

[12] Secure access to the APS is via the UK Data Service Secure Lab https://ukdataservice.ac.uk/help/secure-lab/what-is-securelab/

dataset containing a representative sample of households and individuals from across the UK. We use data from 2019, selected as the most recent pre-pandemic year.[13] We retain individuals between the ages of 25 and 64 for the analysis; this age range is chosen to include people who are of working age, but who are likely to have completed their full-time education.

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

It is important to note that not all employment is the same. The experience of people in employment can vary substantially in terms of number of hours worked, earnings, job security and other aspects of job quality. There is much evidence to suggest that employed disabled people on average have worse outcomes than employed non-disabled people. For example, as discussed above, there is a substantial disability wage gap in the UK (Kidd et al., 2000; Longhi et al., 2012). In our sample, 34% of employed disabled people work part time compared to 23% of employed non-disabled people. However, we do not take account of different types of work as this is beyond the scope of this paper. Moreover, while being in part time work can be more precarious, this can also be conducive to a work-life balance thus providing an enhanced employment experience, particularly for disabled people (and especially those who need to manage chronic conditions).

Our 'treatment' variable D_i is disability. Disability is defined according to the Equality Act (2010).[14] A person is deemed to be disabled ($D_i = 1$) if they report having any health problems or illnesses lasting 12 months or more and say that this reduces their ability to carry out day-to-day activities. They are otherwise classified as non-disabled ($D_i = 0$).

The disabled population can be classified further into whether their condition is related to physical health, mental health or both. Table A4 shows the different health conditions covered in the APS survey and how they are categorised into physical and mental health conditions. Many disabled people have more than one health condition and hence some people in our sample have both physical and mental health conditions. Note that if an individual fits the criteria for disability but reports only having 'other health problems or disabilities', then they are defined as being disabled (in terms of the overall DEG) but are removed from the analysis

[13] Running the same analysis for other years gives similar results.

[14] Note that even though the Equality Act does not apply to Northern Ireland, our definition of disability is the same across all four countries of the UK.

relating specifically to physical and mental health conditions. We also classify the disabled population into severity of impairment; this is determined by whether the individual reports that their health problem reduces their ability to carry out day-to-day activities ‘a lot’ or ‘a little’.

From the APS individual and household-level datasets, we can also identify several other characteristics. Our key characteristic of interest is education ($\mathbf{q}_i$). We identify the highest qualification attained by each individual, differentiating between vocational and academic qualifications. While academic qualifications offer comprehensive subject knowledge and generic skills, vocational qualifications emphasise technical and procedural knowledge and skills, which are often relevant to specific occupational roles (Espinoza and Speckesser, 2019). In the UK, qualifications are classified into levels with vocational and academic qualifications situated at each level. Table A1 in the appendix shows how (following McIntosh and Morris, 2021) we classify each of the 84 qualifications identified in the APS into one of 11 mutually exclusive highest qualification levels.

We also control for a number of other characteristics to make up $\mathbf{x}_i$, including sex and age, where the sample is divided into three age groups: 25-34, 35-49 and 50-64. To define marital status, an individual is considered to be married/cohabiting if they are either married, cohabiting or in a civil partnership. Individuals not living with a partner (e.g. single, widowed, separated, divorced or formerly in a civil partnership) are defined as non-married. We create four dummy variables to identify whether there are any dependent children in the household aged under 2, 2-4, 5-9 and 10-15 respectively. We would expect marriage and the presence of children to have differential effects on employment for women and men. To account for this, we interact the marital status dummy and the four children dummies with sex to create a further five dummy variables. Individuals are also classified into one of the following six ethnic groups: White, Mixed/Multiple ethnic groups, Indian, Pakistani, Black/African/Caribbean/Black British and Other (which includes Bangladeshi, Chinese, Any other Asian background and Other ethnic group).

We use the APS Household dataset (Office for National Statistics, 2021) to observe the employment status of the individual’s partner, creating two dummy variables to identify whether they have a partner who is unemployed or economically inactive respectively. Note that both of these dummy variables are zero if either the individual has an employed partner or does not have a partner. The small number of individuals known to have a partner but where the partner’s employment status is unknown are dropped from the sample. We use five categories to define housing tenure: owned outright; being bought with mortgage or loan; part rent, part mortgage; rented; and rent free. A final dummy variable identifies whether or not the individual lives in an urban area. For England, Scotland and Wales, this is provided as a derived variable in APS (simplified from a more stratified urban/rural classification). Due to more limited spatial information in APS for Northern Ireland residents, we classify these individuals into urban/rural based more crudely on their NUTS3 area of residence. We include a full set of area dummy variables denoting the local authority (district and unitary in England) in which the individual lives. Northern Ireland is considered a single area for this analysis as APS does not record local authority of residence for people living in Northern Ireland.

5. Results

5.1 Overall DEG

The overall DEG in 2019 was 33 percentage points (pp). This is the difference between the employment rates of non-disabled ($\bar{y}^0 = 86\%$) and disabled ($\bar{y}^1 = 53\%$) people. As shown in Figure 1, the employment rates of disabled people are lower than those of non-disabled people at all levels of education. However, there is a much a steeper education-employment gradient for disabled people; the DEG is much smaller at higher qualification levels, ranging from 16pp among those educated to degree level to 48pp among those with no qualifications. While non-disabled people with no qualifications have an employment rate just 17pp below non-disabled people with a degree, the gap between disabled people with no qualifications and disabled people with a degree is 50pp. Apart from degree level, the DEGs for people holding a vocational qualification as their highest tend to be slightly smaller than the DEGs for people holding an academic qualification at the same level.

Figure 2 shows a descriptive representation of how the overall DEG of 33pp can be attributed between the different qualification levels. This is an unconditional version of equation (6), in which the size of each segment is calculated by taking the product of the qualification level DEG and the proportion of disabled people with that highest qualification, and dividing this by the overall DEG. We can see from this simple representation that people with no qualifications account for a quarter of the DEG (so that if the DEG were eliminated among people with no qualifications, the overall DEG would drop by a quarter). The second most important qualification level is GCSE grades A*-C, while degree level is the third most important. Even though the DEG is relatively small among degree holders, the fact that a relatively high proportion of people hold a degree means that it still makes an important contribution to the overall DEG.

The means of each highest qualification among disabled and non-disabled people, and the coefficients from the individual equations where highest qualification is normalised, as per equation (2), are shown in Table 1. For comparison, the means and coefficients of all other variables in the model (excluding local areas) are shown in Table A5. The respective means show that there are large differences in the qualification levels of disabled and non-disabled people. Nearly two-fifths (39%) of non-disabled people are educated to degree level or higher compared to less than a quarter (24%) of disabled people. Disabled people are nearly three times as likely not to have any qualifications (17%, compared to 6% of non-disabled people). Across the other qualification levels, the distribution is more similar between the two groups (although disabled people are also under-represented among those who achieve Level 4+ vocational qualifications or AS/A levels). Nevertheless, the large differences at the two extreme ends of the distribution indicate a substantial gap in educational attainment between disabled and non-disabled people.

There are also clear differences in the estimated coefficients from the disabled and non-disabled equations. For non-disabled people, holding a degree increases the probability of employment by only 3.5pp relative to the average return across all qualification levels, and there is very little difference between holding a degree and having a high-level vocational qualification or apprenticeship. Among disabled people, however, holding a degree increases the probability of employment by 13.3pp and this is markedly higher than having a good vocational qualification. Disabled people also suffer a larger employment penalty from having lower qualification levels, including 3.4pp lower employment for holding GCSEs at grade A*-C as their highest and 6.2pp lower for holding GCSEs at grade D-G, relative to the average return across all qualifications. Non-disabled people experience no such penalty. Having no qualifications is associated with an 18.5pp lower employment rate for disabled people but only 8.4pp for non-disabled people.

Table 2 shows the decomposition of the DEG into characteristics and structural components as per equations (4) and (5) respectively. The results including all covariates (not just education) are reported in Table A6. Note that the sum of the characteristics component (split between education and other characteristics) and the structural component add up to the DEG. The first column of results in Table 2 shows the decomposition under the assumption that the counterfactual employment structure is that of non-disabled people. We can see that the structural component accounts for most of the DEG (28.2pp or 85%). In principle, therefore, removing structural barriers alone, without any change in qualification levels or other observed characteristics, would reduce the DEG from 33pp to just 5pp. Having fully removed structural barriers, a further gain of 1.4pp (4% of the DEG) could be achieved if disabled people had the same levels of education on average as non-disabled people. This would mainly involve reducing the number of disabled people with no qualifications (closing the DEG by up to 0.9pp) and increasing the number of disabled people with degrees (closing the DEG by up to 0.5pp). A gap of 3.6pp (11% of the original DEG) would remain due to differences in non-modifiable characteristics.

An interpretation of the last column in Table 2, where the counterfactual employment structure is that of disabled people, involves telling a somewhat different story. In this case, we assume that policy is initially focused on educational investment. We can see that, if all structural barriers remain in place, it would in principle be possible to reduce the DEG by 4.1pp (12%) by improving the education of disabled people such that they have the same qualifications on average as non-disabled people. Again, the biggest contributions would come from equalising the proportions with degrees (2.0pp) and no qualifications (1.9pp). However, we assume it would not be possible to address the 10.7pp gap explained by differences in other characteristics. Having achieved parity in education, policy would then focus on addressing structural barriers to ensure that disabled people enjoy the same probability of employment as similarly qualified non-disabled people. Removing all structural barriers would reduce the DEG by a further 18.4pp (55%).

Comparing the percentage contributions at the bottom of Table 2, it is clear that using disabled people's employment structure as the counterfactual leads to larger estimates of the characteristics components. This is because the returns to many characteristics, and certainly most qualifications, are larger for disabled than non-disabled people. We explore the intuition behind this result in the Discussion and Conclusion section below. As noted above, the return to a degree and the penalty for having no qualifications are both much larger for disabled people. This implies, paradoxically, that improvements in disabled people's education would have more impact in a counterfactual world of structural barriers to disabled people's employment (equation (5)) than in a world without barriers (equation (4)). In practice, policy aims to reduce barriers but eliminating them completely is not realistic. Hence, the likely impact on the DEG of improving disabled people's education lies between the two alternative estimates of Table 2.[15]

Table 3 shows how the structural component of the DEG can be attributed to each qualification level, following equations (6) to (9). Where the structural component is weighted by the mean

[15] Alternative decompositions can be produced that use intermediate values for the counterfactual employment structure; these lie between the range of values reported in Table 2. See Table A2.

qualification levels of disabled people (equivalent to using the non-disabled coefficients to value the characteristics component), such that there is no change in the education levels of disabled people, the greatest gains can be made among people with no qualifications. Removing structural barriers for this group only, such that disabled people with no qualifications are just as likely to be employed as non-disabled people with no qualifications, would in itself reduce the DEG by 6.5pp (23% of the structural component). A further 5.2pp (18%) reduction would be achieved by removing structural barriers for people with GCSEs A*-C as their highest qualification and a further 4.6pp (16%) would result from removing structural barriers for people with a degree.

The last two columns of Table 3 show the attribution of the structural component between highest qualification levels when weighted by the mean qualification levels of non-disabled people (equivalent to using the disabled coefficients for the characteristics component). In this case, it is assumed that parity in education has first been achieved before tackling structural barriers, and hence a much larger percentage of the disabled population would hold a degree. Even though the employment gap is relatively small among degree holders, the removal of structural barriers among this group would bring about the largest reduction to the structural component (4.8pp or 26%).

Table A3 shows the breakdown of the structural component using the conventional method where the highest qualification variable is normalised and where academic degree and no qualifications respectively are the omitted categories. This shows that the decomposition results are vastly different depending on how the qualifications vector is specified, with changes of both magnitude and sign in the education component, supporting our approach of apportioning the full structural component between qualifications.

5.2 DEGs by demographic groups

Acknowledging that there is not simply one relevant DEG, we now explore decompositions of other DEGs defined by different individual characteristics. Table 4 shows the decomposition of the female and male DEGs. Overall the gap is wider for males (36.8pp) than females (29.4pp). This is due to non-disabled males having a much higher employment rate than non-disabled females, while the employment rate of disabled males is more similar to that of disabled females. A policy aimed at removing structural barriers without first addressing educational inequality would reduce the male and female DEGs by a similar percentage (86-87%). Attributing this structural component across qualifications (not shown in the tables), we find that targeting people with no qualifications would have more impact for males (reducing the gap by 8.1pp) than for females (5.3pp), where proportionally more of the structural inequalities exist further up the qualification distribution. A policy aimed at achieving educational parity without first addressing structural barriers would have a greater effect on the female DEG (16%) than the male DEG (9%). For both sexes, reducing the number of disabled people with no qualifications and increasing the number of disabled people with degrees would have the most impact, but improving the qualification levels of those in the middle of the educational distribution would also have an impact particularly for females, as the employment penalty for not having a degree is higher among disabled females than disabled males.

It is also possible that the relationship between disability, employment and education may vary according to age. Table 5 shows that people over the age of 50 are much less likely than younger people to have a degree. They are also slightly more likely to have no qualifications. Table 6 shows that the DEG is larger for older people, rising from 28pp among 25-34 year olds to 34pp among 50-64 year olds. Education also explains more of the DEG for younger people. Achieving parity of education without addressing structural barriers would reduce the DEG by 5.1pp (18%) for 25-34 year olds but just 2.7pp (8%) for 50-64 year olds. For the youngest age group, achieving parity in the proportion of people with a degree would have the most effect (3.1pp) but the effect would be negligible (0.8pp) for the oldest age group. The extent to which reducing the number of disabled people with no qualifications would affect the DEG is similar for all three age groups. Removing structural barriers without changing education profile or other characteristics would have the largest effect on the oldest age group (31.9pp or 93% of the DEG) and the smallest effect on the youngest age group (23.1pp or 84% of the DEG). Eliminating structural barriers for those with no qualifications only would have the largest effect on the 50-64 age group, accounting for 26% of the overall structural gap (not shown in the tables).

5.3 DEGs by health conditions

We now turn to the separate DEGs for people with mental and physical health conditions respectively, remembering that some disabled people are in both groups. As shown in Table 7, the mental health DEG (46.3pp) is higher than that for physical health (34.2pp). Removing structural barriers would have a greater impact on the mental health DEG (41.1pp) than the physical health DEG (28.8pp), and again targeting those with no qualifications would make the most difference for both groups. A policy focused on achieving education parity should again prioritise improving the education of disabled people with no qualifications and helping more disabled people gain degree level qualifications, and this is the case for both the mental health and physical health DEGs.

As one would expect, disabled people with a more severe impairment have much lower employment rates than disabled people with a less severe impairment. Hence there is a big difference in the DEGs (57.1pp compared to 13.9pp), as shown in Table 8. While removing structural barriers would decrease the more severe DEG by 49.9pp (87% of the DEG), this would only decrease the less severe DEG by 10.8pp (78% of the DEG). Among disabled people with more severe impairments, structural barriers are particularly significant for those with no qualifications and achieving an equitable employment structure for this group alone would reduce the more severe DEG by 13.7pp. In contrast, a complete removal of structural barriers for people with no qualifications would reduce the less severe DEG by just 1.7pp while targeting those with degrees would reduce the less severe DEG by 2.3pp (not shown in the tables). Achieving education parity would also disproportionately help those with more severe impairments, reducing the more severe DEG by 6.2pp and the less severe DEG by 1.1pp, as shown in Table 8. In both cases, most of this reduction would be achieved by decreasing the number of disabled people with no qualifications and increasing the number of disabled people with degrees.

5.4 DEGs by labour market preferences and attachment

Individual preferences potentially have an important role to play in the DEG, and this is a factor that is rarely, if ever, explored in the existing empirical literature. Work may not be appropriate for everyone of working age, particularly disabled people with more severe impairments. Therefore, even in an ideal world we would expect a DEG to exist. In this paper, we try to take account of this by defining a preference-based DEG, where people expressing a preference not to work are removed from the analysis.[16] Excluding such people should be done with caution as stating a preference not to work does not necessarily indicate that a person is not able to work or would not benefit from being in employment. Indeed, many such people could be experiencing ‘hidden unemployment’ as identified by Beatty et al. (2022). Nevertheless, although the preference-based DEG is smaller than the overall DEG, a gap still exists (16.6pp), demonstrating that, even among those who say they want to work, disabled people are still significantly less likely to be employed.

[16] It is assumed that individuals currently in work, unemployed or looking for work have a preference for work. Individuals who are inactive and not looking for work are asked whether they would like to have a regular paid job, either full-time or part-time. Those answering ‘yes’ to that question are also assumed to have a preference for work while those answering ‘no’ are removed from the sample used to estimate the preference-based DEG.

An alternative way to differentiate people who are close to the labour market from those who are more detached is to observe how long ago they last worked. If we remove everyone who left their last job more than 12 months ago (or have never worked), the DEG falls to 4.0pp. If we remove everyone who left their last job more than five years ago (or have never worked), the DEG is 14.2pp. We define these DEGs as the ‘strongly attached’ and ‘weakly attached’ DEGs respectively.

We decompose these different DEGs in Table 9. This is informative for a policy that seeks only to improve the employment prospects of disabled people who are close to the labour market. Compared to the overall DEG, a policy aimed at eliminating structural barriers would be relatively more effective at tackling the preference-based DEG, reducing it by 15.2pp (92%) without changing qualifications or other characteristics.

Table 9 shows that investing in education without addressing structural barriers is predicted to have a relatively small effect on the preference-based DEG (1.3pp or 8%). Again most of this investment should be focused on improving the education of disabled people with no qualifications and helping more disabled people gain degree level qualifications. Investing in education would have an even smaller effect on the ‘strongly attached’ DEG (0.1pp or 3%) and the ‘weakly attached’ DEG (0.8pp or 5%), although other characteristics do explain a larger share of the gap.

Unlike the overall DEG, where reducing structural barriers for people with no qualifications would have the most effect, a policy aimed at reducing the DEG for people more attached to the labour market should focus on addressing structural barriers for people with a degree, as degree holders make up a much larger share of the disabled population in these more attached groups. This is shown in Table 10.

6. Discussion and Conclusion

This paper provides new insights on the importance of education to the DEG in the UK. By decomposing the gap in different ways, we demonstrate the potential impact of different policy options. Our results suggest that investing in disabled people’s education will help to reduce the DEG. However, the overall impact of such policies, if not accompanied by efforts to tackle structural inequalities in the labour market, is likely to be relatively small.

We show that if disabled people could achieve qualification levels equal to those of non-disabled people, this would by itself reduce the gap by 12%,[17] an effect that would be greater for females than males. This result is comparable to a recent study using a different methodology, where removing the education gap is predicted to reduce the DEG among 25-34 year-olds in the European Union by 20% (Albinowski et al., 2023). In contrast, the DEG would be reduced by 85% if policies aimed at reducing structural barriers were to result in disabled people being employed at the same rate as non-disabled people conditional on their qualifications and other characteristics.[18] This impact would be even greater for disabled people with mental health conditions and disabled people with more severe impairments.

The decomposition literature traditionally points to the existence of an 'unexplained' or structural gap as evidence of discrimination but, when applied to the DEG, the interpretation is not that straightforward. As discussed above, in the biopsychosocial model a disabled person's ability to access employment is partly due to their impairments (supply) and partly due to the disabling effects of the labour market environment (demand), in which discrimination may play a role.

Moreover, the structural component of the overall DEG also reflects individuals' preferences. This paper shows that relatively more disabled people than non-disabled people state a preference not to work. If the DEG were to be redefined such that people with a stated preference not to work were removed entirely from the pool of potential labour supply, the effect would be to halve the DEG from 33pp to 17pp. Arguably, reducing this smaller 'preference-based' DEG, or a similar DEG restricted only to those with recent labour market experience, is a more appropriate and achievable target for government policy. Our analysis suggests that addressing structural barriers is just as important (if not more so) for targeting the DEG among people with high labour market attachment as it is for the overall DEG.

While we cannot identify the structural barriers themselves, our analysis does provide insights into how they vary across different levels of education. We find that almost a quarter of the total structural component of the DEG is attributed to people with no qualifications, even though this group accounts for just 17% of disabled people. This is due to the difference in coefficients being particularly large for this group, such that the employment penalty for having no qualifications is much higher for disabled people than for non-disabled people. In other words, gaining qualifications seems to matter more for the employment prospects of disabled people than non-disabled people. We can put forward several possible reasons for this.

[17] Based on the decomposition in equation (5).
[18] Based on the decomposition in equation (4).

Firstly, as disabled people tend to face more barriers in education, those who do attain a good education may have other qualities (not observed in the data) leading them to be particularly employable, such as motivation and resilience or strong support from family and social networks. Related to this point, disabled people with less severe impairments or a later onset of disability are likely to face lower barriers to both education and employment, hence educational attainment is a marker for severity or later onset and may explain why poorly educated disabled people have such low levels of employment. As non-disabled people have no or minimal impairments, this would not explain their educational attainment or employability. We find that the relationship between qualifications and employment is less steep when splitting the sample by severity.

Secondly, higher qualifications allow people to access jobs which are more disability friendly and have fewer barriers. Good qualifications also make it easier for people to change jobs or even drop down to a lower grade job if they need to, without having to leave employment altogether (Baumberg, 2015; Cutler et al., 2006).

Thirdly, due to the existence of statistical discrimination, many disabled people may feel they need to gain qualifications in order to counter discrimination (Dickerson et al., 2022). Faced with imperfect information about the qualities of job applicants, employers may interpret the presence of a disability as a signal of lower productivity. Disabled people can offset this discrimination by using formal qualifications to signal their productivity. Hence we might expect employers to discriminate less on the basis of disability among candidates with higher qualifications.

Since 2015, all young people in England must continue to participate in education until the age of 18 (HM Government, 2011). While this does not guarantee that everybody leaves full time education with a qualification, over time this should reduce the number of working age adults with no qualifications and limit the intersectional disadvantage of being disabled and having no qualifications, although further targeted investment is required to enable disabled people to attain higher level qualifications at the same rate as non-disabled people. A bigger challenge, however, is to address the DEGs that exist among people with the same education levels. Further research is required to understand the extent to which discrimination or other demand-side factors are driving these inequalities.

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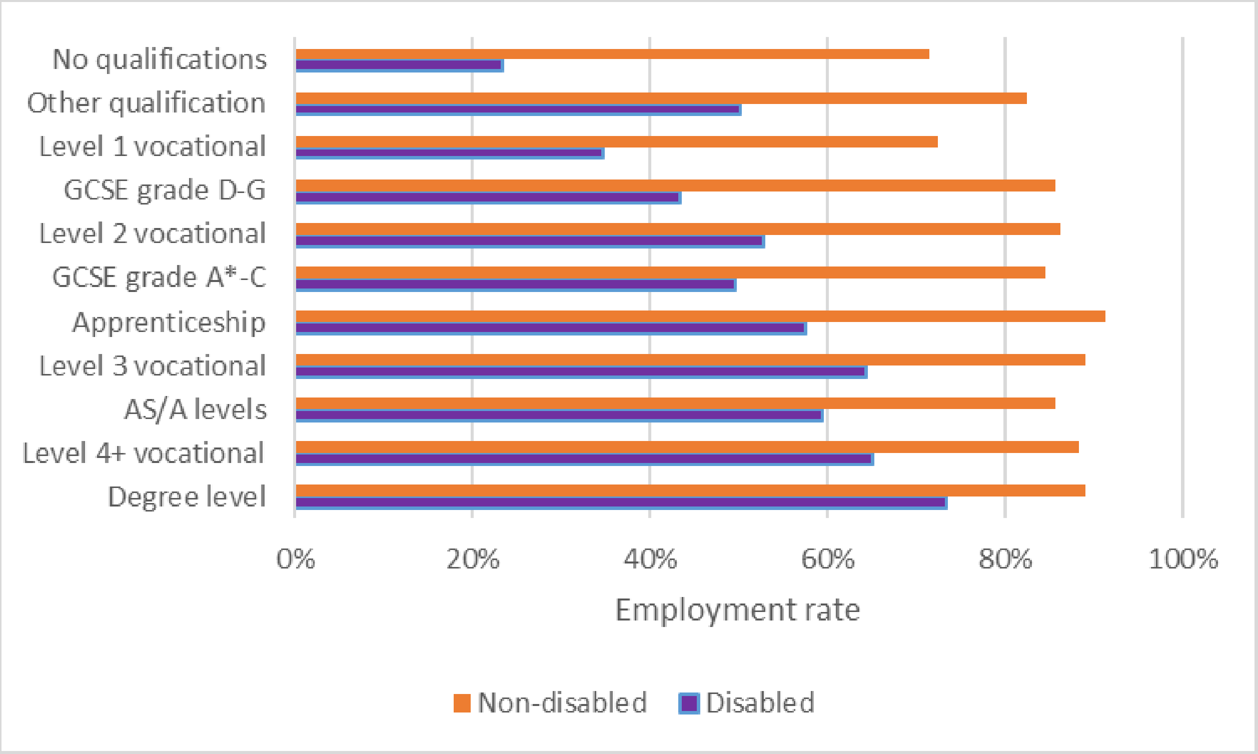
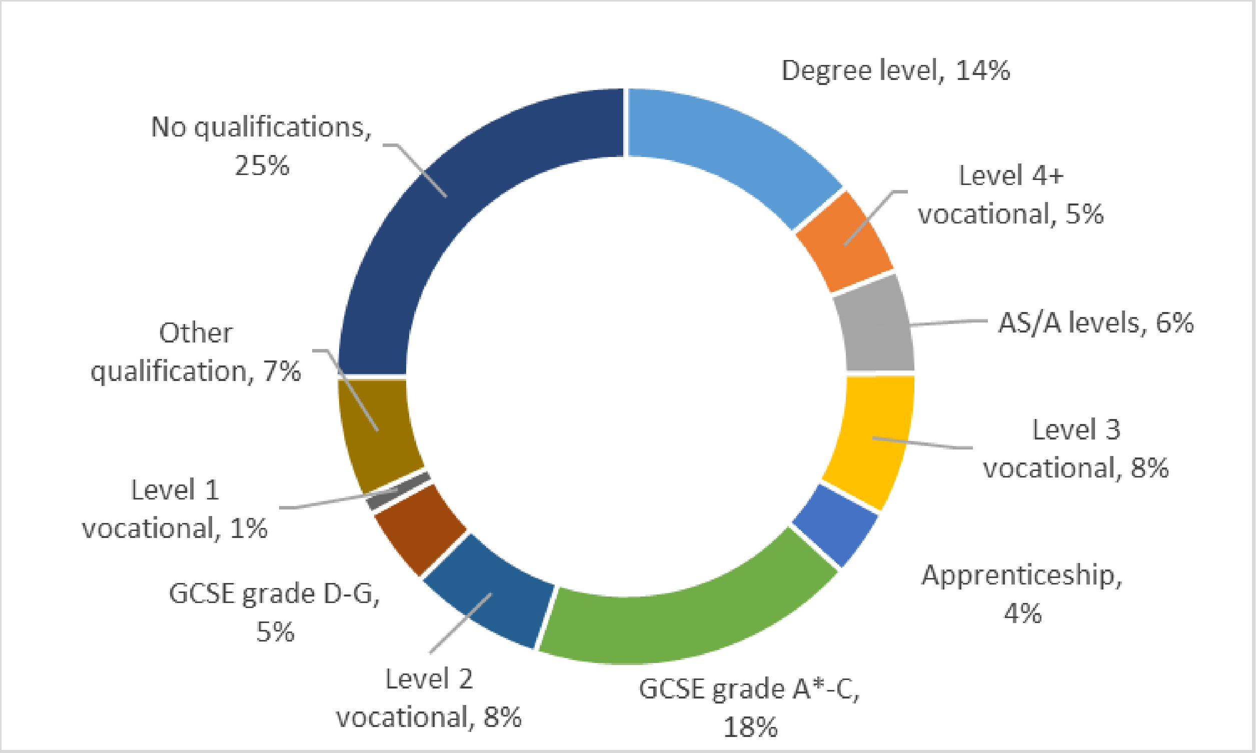
Figures

Figure 1 – Employment rates by highest qualification, 2019



Source: Annual Population Survey

Figure 2 – Descriptive decomposition of the DEG into qualification levels, 2019



Source: Annual Population Survey

Tables

Table 1 – Means and estimated coefficients of highest qualification

Highest qualification	Non-disabled people		Disabled people	
	Mean	Coefficient	Mean	Coefficient
	$\bar{q}_k^0$	$\hat{\beta}_{q_k}^0$	$\bar{q}_k^1$	$\hat{\beta}_{q_k}^1$
Degree level	0.388**	0.035**	0.237**	0.133**
	(0.002)	(0.003)	(0.002)	(0.006)
Level 4+ vocational	0.078**	0.031**	0.074**	0.082**
	(0.001)	(0.004)	(0.002)	(0.009)
AS/A levels	0.072**	0.001	0.061**	0.033**
	(0.001)	(0.004)	(0.001)	(0.010)
Level 3 vocational	0.096**	0.033**	0.099**	0.093**
	(0.001)	(0.004)	(0.002)	(0.008)
Apprenticeship	0.033**	0.034**	0.036**	0.015
	(0.001)	(0.005)	(0.001)	(0.013)
GCSEs grade A*-C	0.142**	-0.002	0.160**	-0.034**
	(0.001)	(0.003)	(0.002)	(0.007)
Level 2 vocational	0.048**	0.023**	0.069**	0.021*
	(0.001)	(0.005)	(0.001)	(0.010)
GCSEs grade D-G	0.022**	0.004	0.031**	-0.062**
	(0.000)	(0.007)	(0.001)	(0.014)
Level 1 vocational	0.004**	-0.079**	0.008**	-0.107**
	(0.000)	(0.015)	(0.001)	(0.026)
Other	0.055**	0.004	0.059**	0.012
	(0.001)	(0.004)	(0.001)	(0.010)
No qualifications	0.063**	-0.084**	0.166**	-0.185**
	(0.001)	(0.004)	(0.002)	(0.007)
N	104,096	104,096	30,007	30,007

* *p*<0.05; ** *p*<0.01; N = 134,103; All other control variables included but not shown.

Table 2 – Decomposition of overall DEG

	Non-disabled as reference Equation (4)	Disabled as reference Equation (5)
DEG	0.3318**	0.3318**
	(0.0031)	(0.0031)
Degree	0.0052**	0.0200**
	(0.0004)	(0.0010)
Level 4+ vocational	0.0002**	0.0004**
	(0.0001)	(0.0001)
AS/A levels	0.0000	0.0004**
	(0.0000)	(0.0001)
Level 3 vocational	-0.0001	-0.0003
	(0.0001)	(0.0002)
Apprenticeship	-0.0001*	-0.0000
	(0.0000)	(0.0000)
GCSEs grade A*-C	0.0000	0.0006**
	(0.0001)	(0.0001)
Level 2 vocational	-0.0005**	-0.0005*
	(0.0001)	(0.0002)
GCSEs grade D-G	-0.0000	0.0006**
	(0.0001)	(0.0002)
Level 1 vocational	0.0003**	0.0004**
	(0.0001)	(0.0001)
Other	-0.0000	-0.0001
	(0.0000)	(0.0001)
No qualifications	0.0086**	0.0190**
	(0.0005)	(0.0008)
Sum of education factors	0.0136**	0.0406**
	(0.0006)	(0.0013)
Other characteristics	0.0360**	0.1073**
	(0.0011)	(0.0023)
Structural component	0.2822**	0.1839**
	(0.0030)	(0.0034)
% education	4%	12%
% other characteristics	11%	33%
% structural	85%	55%
N	134,103	134,103

* *p*<0.05; ** *p*<0.01

Table 3 - Attribution of the structural component to qualification levels

	Weighted by disabled means $\bar{q}_k^1$			Weighted by non-disabled means $\bar{q}_k^0$		
	Structural component $\Delta^s_{q_k^1}$	Attribution (pp) $\bar{q}_k^1\Delta^s_{q_k^1}$	Attribution (%) $\bar{q}_k^1\Delta^s_{q_k^1}/\Delta^s_{q^1}$	Structural component $\Delta^s_{q_k^0}$	Attribution (pp) $\bar{q}_k^0\Delta^s_{q_k^0}$	Attribution (%) $\bar{q}_k^0\Delta^s_{q_k^0}/\Delta^s_{q^0}$
Degree	0.194**	0.046**	16%	0.123**	0.048**	26%
	(0.006)	(0.001)		(0.005)	(0.002)	
Level 4+ vocational	0.242**	0.018**	6%	0.171**	0.013**	7%
	(0.011)	(0.001)		(0.011)	(0.001)	
AS/A levels	0.260**	0.016	6%	0.189**	0.014**	7%
	(0.011)	(0.001)		(0.011)	(0.001)	
Level 3 vocational	0.233**	0.023**	8%	0.162**	0.016**	8%
	(0.009)	(0.001)		(0.009)	(0.001)	
Apprenticeship	0.312**	0.011**	4%	0.241**	0.008**	4%
	(0.015)	(0.001)		(0.015)	(0.001)	
GCSEs grade A*-C	0.324**	0.052**	18%	0.253**	0.036**	19%
	(0.007)	(0.001)		(0.008)	(0.001)	
Level 2 vocational	0.295**	0.020**	7%	0.223**	0.011**	6%
	(0.011)	(0.001)		(0.012)	(0.001)	
GCSEs grade D-G	0.359**	0.011**	4%	0.287**	0.006**	3%
	(0.016)	(0.001)		(0.016)	(0.001)	
Level 1 vocational	0.321**	0.003**	1%	0.250**	0.001**	1%
	(0.035)	(0.000)		(0.035)	(0.000)	
Other	0.285**	0.017**	6%	0.214**	0.012**	6%
	(0.013)	(0.001)		(0.013)	(0.001)	
No qualifications	0.394**	0.065**	23%	0.322**	0.020**	11%
	(0.008)	(0.002)		(0.009)	(0.001)	
Total	-	0.282	100%	-	0.184	100%
		(0.003)			(0.003)	

* p<0.05; ** p<0.01; N = 134,103; Bootstrapped standard errors in brackets

Table 4 – Decomposition of female and male DEGs

	Female		Male	
	Non-disabled as reference Equation (4)	Disabled as reference Equation (5)	Non-disabled as reference Equation (4)	Disabled as reference Equation (5)
DEG	0.2944**	0.2944**	0.3682**	0.3682**
	(0.0041)	(0.0041)	(0.0047)	(0.0047)
Degree	0.0096**	0.0248**	0.0003	0.0140**
	(0.0007)	(0.0015)	(0.0005)	(0.0015)
Level 4+ vocational	-0.0000	-0.0000	0.0001	0.0008**
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
AS/A levels	0.0001	0.0002	-0.0000	0.0006*
	(0.0001)	(0.0001)	(0.0001)	(0.0002)
Level 3 vocational	-0.0003	-0.0005	-0.0000	-0.0001
	(0.0001)	(0.0003)	(0.0001)	(0.0002)
Apprenticeship	-0.0001	-0.0001	-0.0004**	-0.0001
	(0.0000)	(0.0001)	(0.0001)	(0.0002)
GCSEs grade A*-C	0.0001	0.0011**	-0.0000	0.0001
	(0.0001)	(0.0003)	(0.0000)	(0.0001)
Level 2 vocational	-0.0010**	-0.0005	-0.0001	-0.0004
	(0.0002)	(0.0003)	(0.0001)	(0.0002)
GCSEs grade D-G	0.0001	0.0011**	-0.0002*	0.0001
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Level 1 vocational	0.0004**	0.0004**	0.0003**	0.0004*
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Other	0.0001*	-0.0000	-0.0002*	-0.0001
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
No qualifications	0.0122**	0.0193**	0.0044**	0.0188**
	(0.0007)	(0.0011)	(0.0006)	(0.0013)
Sum of education factors	0.0212**	0.0458**	0.0041**	0.0341**
	(0.0010)	(0.0019)	(0.0007)	(0.0020)
Other characteristics	0.0213**	0.0728**	0.0439**	0.1392**
	(0.0017)	(0.0029)	(0.0014)	(0.0038)
Structural component	0.2519**	0.1758**	0.3202**	0.1949**
	(0.0040)	(0.0044)	(0.0046)	(0.0051)
% education	7%	16%	1%	9%
% other characteristics	7%	24%	12%	38%
% structural	86%	60%	87%	53%
N	71,308	71,308	62,795	62,795

* *p*<0.05; ** *p*<0.01

Table 5 – Distribution of highest qualification by age group

	Age 25-34		Age 35-49		Age 50-64	
	Number	%	Number	%	Number	%
Degree	12,139	42%	20,229	41%	15,126	27%
Level 4+ vocational	1,416	5%	3,612	7%	5,334	10%
AS/A levels	2,562	9%	3,178	6%	3,600	7%
Level 3 vocational	3,074	11%	5,007	10%	4,893	9%
Apprenticeship	723	3%	1,244	2%	2,544	5%
GCSEs grade A*-C	3,301	11%	6,204	12%	10,038	18%
Level 2 vocational	1,745	6%	2,836	6%	2,449	4%
GCSEs grade D-G	542	2%	1,020	2%	1,631	3%
Level 1 vocational	145	1%	238	0%	274	0%
Other	1,490	5%	2,995	6%	2,987	5%
No qualifications	1,673	6%	3,361	7%	6,493	12%
Total	28,810	100%	49,924	100%	55,369	100%

Table 6 – Decomposition of DEGs for different age groups

	Age 25-34		Age 35-49		Age 50-64	
	Non-disabled as reference Equation (6)	Disabled as reference Equation (7)	Non-disabled as reference Equation (6)	Disabled as reference Equation (7)	Non-disabled as reference Equation (6)	Disabled as reference Equation (7)
DEG	0.2765**	0.2765**	0.3024**	0.3024**	0.3421**	0.3421**
	(0.0077)	(0.0077)	(0.0053)	(0.0053)	(0.0045)	(0.0045)
Degree	0.0101**	0.0308**	0.0086**	0.0262**	-0.0011*	0.0084**
	(0.0009)	(0.0028)	(0.0006)	(0.0019)	(0.0005)	(0.0011)
Level 4+ vocational	-0.0003	-0.0005	0.0001	0.0004	0.0002	0.0006*
	(0.0003)	(0.0006)	(0.0001)	(0.0004)	(0.0001)	(0.0003)
AS/A levels	-0.0000	-0.0000	0.0002*	0.0003	-0.0004**	0.0001
	(0.0001)	(0.0003)	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Level 3 vocational	-0.0006	-0.0011	-0.0006**	-0.0018**	0.0001	0.0005*
	(0.0003)	(0.0006)	(0.0002)	(0.0004)	(0.0001)	(0.0002)
Apprenticeship	0.0000	0.0000	0.0000	0.0000	-0.0000	0.0000
	(0.0001)	(0.0002)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
GCSEs grade A*-C	-0.0002	0.0021**	-0.0000	0.0006	-0.0001	-0.0004*
	(0.0002)	(0.0007)	(0.0001)	(0.0004)	(0.0001)	(0.0002)
Level 2 vocational	-0.0012**	0.0002	-0.0003	-0.0001	-0.0005**	-0.0007**
	(0.0004)	(0.0008)	(0.0002)	(0.0005)	(0.0001)	(0.0002)
GCSEs grade D-G	0.0001	0.0013*	0.0002	0.0007**	-0.0001	0.0003*
	(0.0002)	(0.0005)	(0.0001)	(0.0003)	(0.0001)	(0.0001)
Level 1 vocational	0.0013**	0.0008	0.0003**	0.0008**	0.0001	0.0001
	(0.0004)	(0.0004)	(0.0001)	(0.0003)	(0.0001)	(0.0001)
Other	-0.0001	-0.0011*	-0.0000	-0.0000	-0.0002	-0.0003
	(0.0001)	(0.0005)	(0.0000)	(0.0001)	(0.0001)	(0.0002)
No qualifications	0.0075**	0.0180**	0.0088**	0.0164**	0.0078**	0.0186**
	(0.0008)	(0.0019)	(0.0006)	(0.0013)	(0.0009)	(0.0013)
Sum of education factors	0.0166**	0.0506**	0.0173**	0.0436**	0.0058**	0.0272**
	(0.0013)	(0.0037)	(0.0009)	(0.0024)	(0.0010)	(0.0017)
Other characteristics	0.0285**	0.0668**	0.0205**	0.1067**	0.0176**	0.0883**
	(0.0025)	(0.0059)	(0.0015)	(0.0042)	(0.0019)	(0.0030)
Structural component	0.2314**	0.1592**	0.2646**	0.1521**	0.3188**	0.2266**
	(0.0073)	(0.0083)	(0.0051)	(0.0058)	(0.0046)	(0.0048)
% education	6%	18%	6%	14%	2%	8%
% other characteristics	10%	24%	7%	35%	5%	26%
% structural	84%	58%	88%	50%	93%	66%
N	28,810	28,810	49,924	49,924	55,369	55,369

* *p*<0.05; ** *p*<0.01

Table 7 – Decomposition of mental and physical health DEGs

	Mental health		Physical health	
	Non-disabled as reference Equation (4)	Disabled as reference Equation (5)	Non-disabled as reference Equation (4)	Disabled as reference Equation (5)
DEG	0.4630**	0.4630**	0.3418**	0.3418**
	(0.0046)	(0.0046)	(0.0034)	(0.0034)
Degree	0.0062**	0.0323**	0.0057**	0.0205**
	(0.0005)	(0.0019)	(0.0004)	(0.0013)
Level 4+ vocational	0.0005**	0.0015**	0.0001	0.0003
	(0.0001)	(0.0003)	(0.0001)	(0.0001)
AS/A levels	0.0000	0.0004*	0.0000	0.0004*
	(0.0000)	(0.0002)	(0.0001)	(0.0002)
Level 3 vocational	-0.0000	-0.0001	-0.0001	-0.0003
	(0.0001)	(0.0003)	(0.0001)	(0.0002)
Apprenticeship	0.0001*	-0.0000	-0.0002**	-0.0000
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
GCSEs grade A*-C	0.0000	0.0011**	0.0000	0.0006**
	(0.0001)	(0.0003)	(0.0001)	(0.0002)
Level 2 vocational	-0.0007**	0.0005	-0.0005**	-0.0005*
	(0.0002)	(0.0004)	(0.0001)	(0.0002)
GCSEs grade D-G	-0.0001	0.0013**	-0.0000	0.0005**
	(0.0001)	(0.0003)	(0.0001)	(0.0002)
Level 1 vocational	0.0005**	0.0003	0.0003**	0.0004**
	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Other	0.0000	-0.0001	-0.0000	-0.0002
	(0.0000)	(0.0001)	(0.0000)	(0.0001)
No qualifications	0.0117**	0.0235**	0.0090**	0.0191**
	(0.0007)	(0.0015)	(0.0005)	(0.0010)
Sum of education factors	0.0183**	0.0606**	0.0142**	0.0406**
	(0.0008)	(0.0025)	(0.0006)	(0.0016)
Other characteristics	0.0336**	0.1303**	0.0397**	0.1144**
	(0.0015)	(0.0045)	(0.0012)	(0.0028)
Structural component	0.4111**	0.2721**	0.2879**	0.1868**
	(0.0045)	(0.0056)	(0.0034)	(0.0039)
% education	4%	13%	4%	12%
% other characteristics	7%	28%	12%	33%
% structural	89%	59%	84%	55%
N	116,522	116,522	127,759	127,759

* *p*<0.05; ** *p*<0.01

Table 8 – Decomposition of ‘more severe’ and ‘less severe’ DEGs

	More severe impairment		Less severe impairment	
	Non-disabled as reference Equation (4)	Disabled as reference Equation (5)	Non-disabled as reference Equation (4)	Disabled as reference Equation (5)
DEG	0.5713**	0.5713**	0.1391**	0.1391**
	(0.0041)	(0.0041)	(0.0037)	(0.0037)
Degree	0.0080**	0.0330**	0.0030**	0.0070**
	(0.0006)	(0.0023)	(0.0003)	(0.0007)
Level 4+ vocational	0.0005**	0.0011**	-0.0001	-0.0002
	(0.0001)	(0.0003)	(0.0001)	(0.0001)
AS/A levels	0.0000	0.0002	0.0000	0.0000
	(0.0001)	(0.0003)	(0.0000)	(0.0000)
Level 3 vocational	0.0002*	0.0005*	-0.0004**	-0.0009**
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Apprenticeship	-0.0001	0.0000	-0.0001*	-0.0001
	(0.0001)	(0.0000)	(0.0001)	(0.0001)
GCSEs grade A*-C	0.0001	0.0012**	0.0000	0.0002
	(0.0001)	(0.0003)	(0.0000)	(0.0001)
Level 2 vocational	-0.0005**	-0.0005	-0.0005**	-0.0002
	(0.0001)	(0.0003)	(0.0001)	(0.0002)
GCSEs grade D-G	-0.0001	0.0010**	-0.0000	0.0002
	(0.0001)	(0.0003)	(0.0000)	(0.0001)
Level 1 vocational	0.0005**	0.0003	0.0002**	0.0003**
	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Other	-0.0000	0.0002	0.0000	0.0001
	(0.0001)	(0.0002)	(0.0000)	(0.0001)
No qualifications	0.0157**	0.0248**	0.0029**	0.0049**
	(0.0008)	(0.0016)	(0.0003)	(0.0005)
Sum of education factors	0.0243**	0.0619**	0.0051**	0.0114**
	(0.0010)	(0.0028)	(0.0004)	(0.0009)
Other characteristics	0.0482**	0.1510**	0.0262**	0.0433**
	(0.0015)	(0.0045)	(0.0011)	(0.0022)
Structural component	0.4989**	0.3584**	0.1078**	0.0844**
	(0.0041)	(0.0057)	(0.0035)	(0.0038)
% education	4%	11%	4%	8%
% other characteristics	9%	26%	18%	32%
% structural	87%	63%	78%	60%
N	117,477	117,477	120,722	120,722

* *p*<0.05; ** *p*<0.01

Table 9 – Decomposition of DEGs based on different measures of labour market attachment

	Preference for work		Strongly attached		Weakly attached	
	Non-disabled as reference Equation (6)	Disabled as reference Equation (7)	Non-disabled as reference Equation (6)	Disabled as reference Equation (7)	Non-disabled as reference Equation (6)	Disabled as reference Equation (7)
DEG	0.1661**	0.1661**	0.0402**	0.0402**	0.1417**	0.1417**
	(0.0030)	(0.0030)	(0.0021)	(0.0021)	(0.0031)	(0.0031)
Degree	0.0021**	0.0091**	-0.0001	0.0008*	0.0003	0.0054**
	(0.0002)	(0.0008)	(0.0001)	(0.0004)	(0.0002)	(0.0007)
Level 4+ vocational	-0.0000	-0.0001	0.0000	-0.0000	-0.0000	-0.0001
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
AS/A levels	0.0001*	0.0002*	-0.0000	0.0000	-0.0001*	0.0001
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Level 3 vocational	-0.0002**	-0.0010**	-0.0000	-0.0001	-0.0001	-0.0006**
	(0.0000)	(0.0002)	(0.0000)	(0.0001)	(0.0001)	(0.0002)
Apprenticeship	-0.0001*	-0.0000	-0.0000	-0.0000	-0.0001*	-0.0000
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
GCSEs grade A*-C	-0.0000	0.0000	0.0000	-0.0000	0.0000	0.0002
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Level 2 vocational	0.0000	-0.0002	0.0000	0.0002	-0.0001	0.0004
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0003)
GCSEs grade D-G	0.0000	0.0005**	-0.0000	0.0000	-0.0001	0.0001
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Level 1 vocational	0.0002**	0.0004**	-0.0000	0.0000	0.0001*	0.0001
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
Other	-0.0000	-0.0001	-0.0000	-0.0000	-0.0000	-0.0001
	(0.0000)	(0.0001)	(0.0000)	(0.0000)	(0.0000)	(0.0001)
No qualifications	0.0011**	0.0040**	0.0001*	0.0003*	0.0001	0.0021**
	(0.0001)	(0.0004)	(0.0001)	(0.0002)	(0.0001)	(0.0003)
Sum of education factors	0.0032**	0.0129**	-0.0000	0.0012**	0.0001	0.0075**
	(0.0002)	(0.0009)	(0.0001)	(0.0004)	(0.0002)	(0.0008)
Other characteristics	0.0108**	0.0487**	0.0044**	0.0069**	0.0160**	0.0350**
	(0.0005)	(0.0019)	(0.0004)	(0.0011)	(0.0007)	(0.0018)
Structural component	0.1522**	0.1046**	0.0358**	0.0321**	0.1256**	0.0991**
	(0.0029)	(0.0032)	(0.0021)	(0.0023)	(0.0030)	(0.0033)
% education	2%	8%	0%	3%	0%	5%
% other characteristics	6%	29%	11%	17%	11%	25%
% structural	92%	63%	89%	80%	89%	70%
N	113,762	113,762	109,259	109,259	117,651	117,651

* p<0.05; ** p<0.01

Table 10 - Attribution of the structural component to qualification levels based on different measures of labour market attachment (weighted by disabled means)

	Preference for work		Strongly attached		Weakly attached	
	Attribution (pp) $\bar{q}_k^1\Delta^s_{q_k^1}$	Attribution (%) $\bar{q}_k^1\Delta^s_{q_k^1}/\Delta^s_{q^1}$	Attribution (pp) $\bar{q}_k^1\Delta^s_{q_k^1}$	Attribution (%) $\bar{q}_k^1\Delta^s_{q_k^1}/\Delta^s_{q^1}$	Attribution (pp) $\bar{q}_k^1\Delta^s_{q_k^1}$	Attribution (%) $\bar{q}_k^1\Delta^s_{q_k^1}/\Delta^s_{q^1}$
Degree	0.031**	21%	0.009**	26%	0.026**	21%
	(0.001)		(0.001)		(0.002)	
Level 4+ vocational	0.010**	7%	0.003**	8%	0.010**	8%
	(0.001)		(0.001)		(0.001)	
AS/A levels	0.009**	6%	0.002**	6%	0.007**	6%
	(0.001)		(0.001)		(0.001)	
Level 3 vocational	0.015**	10%	0.004**	12%	0.013**	11%
	(0.001)		(0.001)		(0.001)	
Apprenticeship	0.007**	5%	0.001**	4%	0.005**	4%
	(0.001)		(0.000)		(0.001)	
GCSEs grade A*-C	0.027**	17%	0.006**	15%	0.023**	18%
	(0.001)		(0.001)		(0.001)	
Level 2 vocational	0.012**	8%	0.003**	9%	0.011**	9%
	(0.001)		(0.001)		(0.001)	
GCSEs grade D-G	0.007**	5%	0.001**	3%	0.004**	4%
	(0.001)		(0.000)		(0.001)	
Level 1 vocational	0.002**	1%	0.000	1%	0.001**	1%
	(0.000)		(0.000)		(0.000)	
Other	0.009**	6%	0.002**	5%	0.007**	6%
	(0.001)		(0.001)		(0.001)	
No qualifications	0.023**	15%	0.004**	10%	0.017**	14%
	(0.001)		(0.001)		(0.001)	
Total	0.152**	100%	0.036**	100%	0.126**	100%
	(0.003)		(0.002)		(0.003)	
N	113,762		109,259		117,651	

* p<0.05; ** p<0.01; Bootstrapped standard errors in brackets

Appendix

Table A1 - Classification of highest qualification (see McIntosh and Morris, 2021)

Highest qualification	**Grouping**
Higher degree	Degree level
NVQ level 5	Level 4+ vocational
Level 8 Diploma	Level 4+ vocational
Level 8 Certificate	Level 4+ vocational
Level 7 Diploma	Level 4+ vocational
Level 7 Certificate	Level 4+ vocational
Level 8 Award	Level 4+ vocational
First degree/foundation degree	Degree level
Other degree	Degree level
NVQ level 4	Level 4+ vocational
Level 6 Diploma	Level 4+ vocational
Level 6 Certificate	Level 4+ vocational
Level 7 Award	Level 4+ vocational
Diploma in higher education	Degree level
Level 5 Diploma	Level 4+ vocational
Level 5 Certificate	Level 4+ vocational
Level 6 Award	Level 4+ vocational
HNC/HND/BTEC higher etc	Level 4+ vocational
Teaching Ð further education	Level 4+ vocational
Teaching Ð secondary education	Level 4+ vocational
Teaching Ð primary education	Level 4+ vocational
Teaching Ð foundation stage	Level 4+ vocational
Teaching Ð level not stated	Level 4+ vocational
Nursing etc	Level 4+ vocational

RSA higher diploma	Level 4+ vocational
Other higher education below degree	Degree level
Level 4 Diploma	Level 4+ vocational
Level 4 Certificate	Level 4+ vocational
Level 5 Award	Level 4+ vocational
NVQ level 3	Level 3 Vocational
Advanced/Progression (14-19) Diploma	Level 3 Vocational
Level 3 Diploma	Level 3 Vocational
Advanced Welsh Baccalaureate	AS/A levels
International Baccalaureate	AS/A levels
Scottish Baccalaureate	AS/A levels
GNVQ/GSVQ advanced	Level 3 Vocational
A-level or equivalent	AS/A levels
RSA advanced diploma	Level 3 Vocational
OND/ONC/BTEC/SCOTVEC National etc	Level 3 Vocational
City & Guilds Advanced Craft/Part 1	Level 3 Vocational
Scottish 6 year certificate/CSYS	AS/A levels
SCE higher or equivalent	AS/A levels
Access qualifications	AS/A levels
AS-level or equivalent	AS/A levels
Trade apprenticeship	Apprenticeship
Level 3 Certificate	Level 3 Vocational
Level 4 Award	Level 3 Vocational
NVQ level 2 or equivalent	Level 2 Vocational
Intermediate Welsh Baccalaureate	GCSEs A*-C
GNVQ/GSVQ intermediate	Level 2 Vocational
RSA diploma	Level 2 Vocational
City & Guilds Craft/Part 2	Level 2 Vocational

BTEC/SCOTVEC First or General diploma etc	Level 2 Vocational
Higher (14-19) Diploma	Level 2 Vocational
Level 2 Diploma	Level 2 Vocational
Level 2 Certificate	Level 2 Vocational
Scottish National Level 5	GCSEs A*-C
O-level, GCSE grade A*-C or equivalent	GCSEs A*-C
Level 3 Award	Level 2 Vocational
NVQ level 1 or equivalent	Level 1 Vocational
Foundation Welsh Baccalaureate	GCSEs D-G
GNVQ/GSVQ foundation level	Level 1 Vocational
Foundation (14-19) Diploma	Level 1 Vocational
Level 1 Diploma	Level 1 Vocational
Scottish National Level 4	GCSEs D-G
CSE below grade 1, GCSE below grade C	GCSEs D-G
BTEC/SCOTVEC First or General certificate	Level 1 Vocational
SCOTVEC modules	Level 1 Vocational
RSA other	Level 1 Vocational
Scottish Nationals Level 3	GCSEs D-G
Scottish Nationals below Level 3	GCSEs D-G
City & Guilds foundation/Part 1	Level 1 Vocational
Level 1 Certificate	Level 1 Vocational
Level 2 Award	Level 1 Vocational
YT/YTP certificate	Other qual
Key skills qualification	Other qual
Basic skills qualification	Other qual
Entry level qualification	Other qual
Entry level Diploma	Other qual
Entry level Certificate	Other qual

Level 1 Award	Other qual
Entry level Award	Other qual
Other qualification	Other qual
No qualifications	No quals
Don’t know	Excluded

Table A2 – Comparison of other decomposition types (overall DEG)

	Sum of education		Total decomposition	
	Characteristics	Structural	Characteristics	Structural
Non-disabled as reference (weight = 1)	0.0136**	-0.0105**	0.0496**	0.2822**
	(0.0006)	(0.0032)	(0.0012)	(0.0030)
Disabled as reference (weight = 0)	0.0406**	-0.0375**	0.1479**	0.1839**
	(0.0013)	(0.0037)	(0.0025)	(0.0034)
Midpoint (weight = 0.5)	0.0271**	-0.0240**	0.0987**	0.2331**
	(0.0008)	(0.0034)	(0.0015)	(0.0030)
Weighted average (weight = 0.78)	0.0196**	-0.0165**	0.0712**	0.2606**
	(0.0006)	(0.0033)	(0.0012)	(0.0029)
Omega model	0.0285**	-0.0254**	0.1034**	0.2284**
	(0.0008)	(0.0035)	(0.0014)	(0.0027)
Pooled model	0.0228**	-0.0197**	0.0784**	0.2534**
	(0.0007)	(0.0035)	(0.0013)	(0.0030)

* $p<0.05$; ** $p<0.01$; DEG=0.3318; N=134,103 for all specifications

Table A3 – Breakdown of structural component

	Highest qualification normalised		Omitting degree		Omitting no qualifications	
	Non-disabled as reference Equation (4)	Disabled as reference Equation (5)	Non-disabled as reference Equation (4)	Disabled as reference Equation (5)	Non-disabled as reference Equation (4)	Disabled as reference Equation (5)
Degree	-0.023**	-0.038**	-	-	-0.0473**	-0.0773**
	(0.002)	(0.003)	-	-	(0.0024)	(0.0038)
Level 4+ vocational	-0.004**	-0.004**	0.0035**	-0.0002*	-0.0111**	-0.0119**
	(0.001)	(0.001)	(0.0009)	(0.0001)	(0.0010)	(0.0010)
AS/A levels	-0.002**	-0.002**	0.0041**	-0.0011**	-0.0082**	-0.0096**
	(0.001)	(0.001)	(0.0008)	(0.0002)	(0.0008)	(0.0010)
Level 3 vocational	-0.006**	-0.006**	0.0039**	0.0001	-0.0159**	-0.0154**
	(0.001)	(0.001)	(0.0010)	(0.0001)	(0.0012)	(0.0011)
Apprenticeship	0.001	0.001	0.0042**	0.0003*	-0.0029**	-0.0027**
	(0.001)	(0.000)	(0.0006)	(0.0001)	(0.0006)	(0.0006)
GCSEs grade A*-C	0.005**	0.004**	0.0207**	0.0030**	-0.0111**	-0.0099**
	(0.001)	(0.001)	(0.0015)	(0.0004)	(0.0017)	(0.0015)
Level 2 vocational	0.000	0.000	0.0069**	0.0024**	-0.0068**	-0.0047**
	(0.001)	(0.001)	(0.0009)	(0.0003)	(0.0009)	(0.0006)
GCSEs grade D-G	0.002**	0.001**	0.0052**	0.0019**	-0.0011*	-0.0008*
	(0.000)	(0.000)	(0.0006)	(0.0003)	(0.0006)	(0.0004)
Level 1 vocational	0.000	0.000	0.0010**	0.0010**	-0.0006*	-0.0003*
	(0.000)	(0.000)	(0.0003)	(0.0002)	(0.0003)	(0.0001)
Other	-0.000	-0.000	0.0054**	0.0005**	-0.0064**	-0.0059**
	(0.001)	(0.001)	(0.0008)	(0.0002)	(0.0008)	(0.0008)
No qualifications	0.017**	0.006**	0.0330**	0.0326**	-	-
	(0.001)	(0.001)	(0.0017)	(0.0012)	-	-
Sum of education factors	-0.011**	-0.037**	0.0879**	0.0609**	-0.1115**	-0.1385**
	(0.003)	(0.004)	(0.0051)	(0.0041)	(0.0070)	(0.0079)
Other characteristics	-0.080**	-0.151**	-0.0797**	-0.1510**	-0.0797**	-0.1510**
	(0.016)	(0.016)	(0.0159)	(0.0159)	(0.0159)	(0.0159)
Constant	0.372**	0.372**	0.2740**	0.2740**	0.4734**	0.4734**
	(0.016)	(0.016)	(0.0167)	(0.0167)	(0.0176)	(0.0176)
Total structural component	0.282**	0.184**	0.2822**	0.1839**	0.2822**	0.1839**
	(0.003)	(0.003)	(0.0030)	(0.0034)	(0.0030)	(0.0034)
N	134,103	134,103	134,103	134,103	134,103	134,103

* $p<0.05$; ** $p<0.01$

Table A4 - Health conditions in APS

Description of condition	Mental or physical? (see Munford et al. 2016)
Problems or disabilities (including arthritis or rheumatism) connected with arms or hands	Physical
Problems or disabilities (including arthritis or rheumatism) connected with legs or feet	Physical
Problems or disabilities (including arthritis or rheumatism) connected with back or neck	Physical
Difficulty in seeing (while wearing spectacles and contact lenses)	Physical
Difficulty in hearing	Physical
A speech impediment	Physical
Severe disfigurement, skin conditions, allergies	Physical
Chest or breathing problems, asthma, bronchitis	Physical
Heart, blood pressure or blood circulation problems	Physical
Stomach, liver kidney or digestive problems	Physical
Diabetes	Physical
Depression, bad nerves or anxiety	Mental
Epilepsy	Physical
Severe or specific learning difficulties (mental handicap)	Mental
Mental illness, or suffer from phobia, panics or other nervous disorders	Mental
Progressive illness not included elsewhere (e.g. cancer, multiple sclerosis, symptomatic HIV, Parkinson's disease, muscular	Physical
Other health problems or disabilities	Neither

Table A5 – Means and estimated coefficients of all covariates

Variable	Non-disabled people		Disabled people	
	Mean	Coefficient	Mean	Coefficient
Degree level	0.388**	0.035**	0.237**	0.133**
	(0.002)	(0.003)	(0.002)	(0.006)
Level 4+ vocational	0.078**	0.031**	0.074**	0.082**
	(0.001)	(0.004)	(0.002)	(0.009)
AS/A levels	0.072**	0.001	0.061**	0.033**
	(0.001)	(0.004)	(0.001)	(0.010)
Level 3 vocational	0.096**	0.033**	0.099**	0.093**
	(0.001)	(0.004)	(0.002)	(0.008)
Apprenticeship	0.033**	0.034**	0.036**	0.015
	(0.001)	(0.005)	(0.001)	(0.013)
GCSEs grade A*-C	0.142**	-0.002	0.160**	-0.034**
	(0.001)	(0.003)	(0.002)	(0.007)
Level 2 vocational	0.048**	0.023**	0.069**	0.021*
	(0.001)	(0.005)	(0.001)	(0.010)
GCSEs grade D-G	0.022**	0.004	0.031**	-0.062**
	(0.000)	(0.007)	(0.001)	(0.014)
Level 1 vocational	0.004**	-0.079**	0.008**	-0.107**
	(0.000)	(0.015)	(0.001)	(0.026)
Other	0.055**	0.004	0.059**	0.012
	(0.001)	(0.004)	(0.001)	(0.010)
No qualifications	0.063**	-0.084**	0.166**	-0.185**
	(0.001)	(0.004)	(0.002)	(0.007)
Female	0.515**	-0.002	0.590**	0.093**
	(0.002)	(0.004)	(0.003)	(0.008)
Age 25-34	0.232**	0.020**	0.156**	0.058**
	(0.001)	(0.002)	(0.002)	(0.005)
Age 35-49	0.389**	0.029**	0.316**	0.014**
	(0.002)	(0.002)	(0.003)	(0.004)
Age 50-64	0.380**	-0.049**	0.528**	-0.072**
	(0.002)	(0.002)	(0.003)	(0.004)
White	0.880**	0.051**	0.905**	0.025**
	(0.001)	(0.003)	(0.002)	(0.009)
Mixed / multiple ethnicity	0.009**	0.039**	0.009**	0.022
	(0.000)	(0.009)	(0.001)	(0.023)
Indian	0.027**	0.020**	0.016**	0.003
	(0.001)	(0.006)	(0.001)	(0.018)
Pakistani	0.018**	-0.083**	0.019**	-0.080**

	(0.000)	(0.007)	(0.001)	(0.018)
Black	0.027**	0.027**	0.020**	0.033*
	(0.001)	(0.006)	(0.001)	(0.017)
Other ethnicity	0.039**	-0.053**	0.032**	-0.004
	(0.001)	(0.005)	(0.001)	(0.014)
Married	0.754**	0.051**	0.587**	0.271**
	(0.001)	(0.004)	(0.003)	(0.009)
Female * Married	0.379**	-0.056**	0.340**	-0.180**
	(0.002)	(0.005)	(0.003)	(0.011)
Children 0-2	0.076**	0.017**	0.035**	0.034
	(0.001)	(0.006)	(0.001)	(0.023)
Female * Children 0-2	0.040**	-0.131**	0.021**	-0.117**
	(0.001)	(0.008)	(0.001)	(0.029)
Children 2-4	0.124**	0.013**	0.071**	0.040*
	(0.001)	(0.005)	(0.001)	(0.018)
Female * Children 2-4	0.066**	-0.133**	0.047**	-0.129**
	(0.001)	(0.007)	(0.001)	(0.022)
Children 5-9	0.193**	0.005	0.127**	0.037*
	(0.001)	(0.004)	(0.002)	(0.015)
Female * Children 5-9	0.105**	-0.087**	0.083**	-0.064**
	(0.001)	(0.005)	(0.002)	(0.018)
Children 10-15	0.199**	0.019**	0.159**	0.057**
	(0.001)	(0.004)	(0.002)	(0.013)
Female * Children 10-15	0.110**	-0.061**	0.104**	-0.064**
	(0.001)	(0.005)	(0.002)	(0.015)
Urban	0.790**	0.004	0.808**	-0.016
	(0.001)	(0.003)	(0.002)	(0.008)
Owned outright	0.249**	-0.064**	0.252**	-0.016
	(0.001)	(0.004)	(0.003)	(0.010)
Bought with mortgage	0.474**	0.064**	0.289**	0.134**
	(0.002)	(0.004)	(0.003)	(0.010)
Part rent / part mortgage	0.006**	0.054**	0.006**	0.057*
	(0.000)	(0.011)	(0.000)	(0.028)
Rented	0.264**	-0.023**	0.445**	-0.106**
	(0.001)	(0.004)	(0.003)	(0.010)
Rent free	0.007**	-0.031**	0.008**	-0.069**
	(0.000)	(0.010)	(0.001)	(0.024)
Partner unemployed	0.011**	-0.061**	0.010**	-0.090**
	(0.000)	(0.010)	(0.001)	(0.026)
Partner inactive	0.120**	-0.167**	0.167**	-0.212**

	(0.001)	(0.003)	(0.002)	(0.008)
N	104,096	104,096	30,007	30,007

* *p*<0.05; ** *p*<0.01; N = 134,103; Categorical variables normalised.

Table A6 – Decomposition of overall DEG (including all covariates)

	Non-disabled as reference Equation (4)		Disabled as reference Equation (5)	
	Characteristics	Structural	Characteristics	Structural
DEG	0.3318**		0.3318**	
	(0.0031)		(0.0031)	
Degree	0.0052**	-0.0234**	0.0200**	-0.0382**
	(0.0004)	(0.0016)	(0.0010)	(0.0027)
Level 4+ vocational	0.0002**	-0.0037**	0.0004**	-0.0039**
	(0.0001)	(0.0008)	(0.0001)	(0.0008)
AS/A levels	0.0000	-0.0020**	0.0004**	-0.0023**
	(0.0000)	(0.0007)	(0.0001)	(0.0008)
Level 3 vocational	-0.0001	-0.0059**	-0.0003	-0.0057**
	(0.0001)	(0.0009)	(0.0002)	(0.0009)
Apprenticeship	-0.0001*	0.0007	-0.0000	0.0006
	(0.0000)	(0.0005)	(0.0000)	(0.0005)
GCSEs grade A*-C	0.0000	0.0050**	0.0006**	0.0044**
	(0.0001)	(0.0012)	(0.0001)	(0.0011)
Level 2 vocational	-0.0005**	0.0001	-0.0005*	0.0001
	(0.0001)	(0.0007)	(0.0002)	(0.0005)
GCSEs grade D-G	-0.0000	0.0021**	0.0006**	0.0014**
	(0.0001)	(0.0005)	(0.0002)	(0.0003)
Level 1 vocational	0.0003**	0.0002	0.0004**	0.0001
	(0.0001)	(0.0002)	(0.0001)	(0.0001)
Other	-0.0000	-0.0005	-0.0001	-0.0004
	(0.0000)	(0.0007)	(0.0001)	(0.0006)
No qualifications	0.0086**	0.0167**	0.0190**	0.0064**
	(0.0005)	(0.0014)	(0.0008)	(0.0005)
Female	0.0002	-0.0561**	-0.0070**	-0.0489**
	(0.0003)	(0.0055)	(0.0007)	(0.0048)
Age 25-34	0.0015**	-0.0059**	0.0043**	-0.0088**
	(0.0001)	(0.0008)	(0.0004)	(0.0012)
Age 35-49	0.0021**	0.0048**	0.0010**	0.0059**
	(0.0001)	(0.0014)	(0.0003)	(0.0017)
Age 50-64	0.0072**	0.0120**	0.0106**	0.0086**
	(0.0003)	(0.0024)	(0.0007)	(0.0017)
White	-0.0013**	0.0234**	-0.0006**	0.0228**
	(0.0001)	(0.0083)	(0.0002)	(0.0081)
Mixed / multiple ethnicity	-0.0000	0.0002	-0.0000	0.0001
	(0.0000)	(0.0002)	(0.0000)	(0.0002)
Indian	0.0002**	0.0003	0.0000	0.0005
	(0.0001)	(0.0003)	(0.0002)	(0.0005)
Pakistani	0.0001	-0.0001	0.0001	-0.0001
	(0.0001)	(0.0004)	(0.0001)	(0.0003)
Black	0.0002**	-0.0001	0.0003	-0.0002
	(0.0001)	(0.0004)	(0.0001)	(0.0005)
Other ethnicity	-0.0004**	-0.0016**	-0.0000	-0.0019**
	(0.0001)	(0.0005)	(0.0001)	(0.0006)

Married	0.0085**	-0.1291**	0.0452**	-0.1659**
	(0.0007)	(0.0060)	(0.0018)	(0.0077)
Female * Married	-0.0022**	0.0419**	-0.0070**	0.0468**
	(0.0003)	(0.0041)	(0.0007)	(0.0046)
Children 0-2	0.0007**	-0.0006	0.0014	-0.0013
	(0.0002)	(0.0008)	(0.0010)	(0.0018)
Female * Children 0-2	-0.0025**	-0.0003	-0.0023**	-0.0006
	(0.0002)	(0.0006)	(0.0006)	(0.0012)
Children 2-4	0.0007**	-0.0019	0.0021*	-0.0034
	(0.0003)	(0.0013)	(0.0010)	(0.0023)
Female * Children 2-4	-0.0026**	-0.0002	-0.0025**	-0.0002
	(0.0002)	(0.0011)	(0.0005)	(0.0015)
Children 5-9	0.0003	-0.0041*	0.0024*	-0.0062*
	(0.0003)	(0.0019)	(0.0010)	(0.0029)
Female * Children 5-9	-0.0019**	-0.0019	-0.0014**	-0.0025
	(0.0002)	(0.0015)	(0.0004)	(0.0020)
Children 10-15	0.0008**	-0.0061**	0.0023**	-0.0076**
	(0.0002)	(0.0021)	(0.0005)	(0.0026)
Female * Children 10-15	-0.0004**	0.0003	-0.0004*	0.0003
	(0.0001)	(0.0017)	(0.0002)	(0.0018)
Urban	-0.0001	0.0158*	0.0003	0.0155*
	(0.0001)	(0.0069)	(0.0002)	(0.0067)
Owned outright	0.0002	-0.0121**	0.0000	-0.0120**
	(0.0002)	(0.0027)	(0.0001)	(0.0027)
Bought with mortgage	0.0117**	-0.0203**	0.0247**	-0.0333**
	(0.0007)	(0.0031)	(0.0019)	(0.0050)
Part rent / part mortgage	0.0000	-0.0000	0.0000	-0.0000
	(0.0000)	(0.0002)	(0.0000)	(0.0002)
Rented	0.0041**	0.0372**	0.0193**	0.0221**
	(0.0007)	(0.0046)	(0.0018)	(0.0027)
Rent free	0.0000	0.0003	0.0001	0.0003
	(0.0000)	(0.0002)	(0.0000)	(0.0002)
Partner unemployed	-0.0001	0.0003	-0.0001	0.0003
	(0.0000)	(0.0003)	(0.0001)	(0.0003)
Partner inactive	0.0078**	0.0075**	0.0099**	0.0054**
	(0.0004)	(0.0014)	(0.0006)	(0.0010)
Sum of areas	0.0011**	0.0168**	0.0046**	0.0133**
	(0.0003)	(0.0032)	(0.0008)	(0.0029)
Constant	-	0.3724**	-	0.3724**
		(0.0165)		(0.0165)
N	134,103		134,103	

* *p*<0.05; ** *p*<0.01; Categorical variables normalised.