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The role of education in the disability employment gap

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Abstract

The gap between the employment rates of disabled and non-disabled people in the UK was 33 percentage points (pp) in 2019. This is partly explained by the fact that disabled people have lower levels of education. To assess the role of education in the disability employment gap (DEG), we decompose this DEG into characteristics and structural components using Oaxaca–Blinder decomposition methods. If the average education levels of disabled people were raised to those of non-disabled people, the DEG could be reduced by 4 pp (12 per cent). This would leave a remaining gap of 11 pp (33 per cent) explained by other characteristics and 18 pp (55 per cent) attributable to structural barriers in the labour market. These results are consistent with other findings in the literature, showing educational inequalities to be an important explanation of the DEG. However, the results also highlight the continued relevance of structural barriers that are disproportionately hindering the employment prospects of disabled people.

Keywords: disability employment gap; decomposition; education
JEL classifications: I14, J14, J24, J71

1. Introduction and background

In 2019 the overall employment rate for disabled people[1] aged between twenty-five and sixty-four in the UK was 53 per cent, compared to 86 per cent for non-disabled people, resulting in a disability employment gap (DEG) of 33 percentage points (pp). While work is not appropriate for all disabled people, the DEG is much wider than similar gaps pertaining to other protected characteristics under the Equality Act (2010); for example, the gender and ethnicity employment gaps were estimated to be 8 pp and 11 pp, respectively, in 2019.[2] While both the academic and policy literature have long recognized the existence of a substantial employment gap between disabled and non-disabled people, there have been very few detailed attempts to unpack the underlying factors behind the DEG. This article makes a fundamental contribution here by decomposing the DEG into the parts due to personal characteristics, structural factors, and the unexplained component. We pay particular

[1] We use the term 'disabled people' throughout this article as this is the language advocated by government, disability charities, and disabled people themselves in a UK context. We recognize that other language, for example, 'people with disabilities', is deemed more appropriate in some countries.

[2] Authors' own calculations from the Annual Population Survey.

attention to education, which has been neglected in the previous literature, but turns out to have a key role to play in the differential employment rates of disabled and non-disabled people.

A full consideration of the socially optimal size of the DEG is beyond the scope of this article, but there are a number of reasons why its current size is 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 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 per cent compared to 17 per cent (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. A target to get 1 million more disabled people into work by 2027 (Department for Work and Pensions and Department of Health 2017) was achieved early.[3] However, an earlier commitment to halve the DEG (Department for Work and Pensions and Department of Health 2016) still remains a long way from being met. 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.

The reasons for this gap are complex and reflect both the relative supply of disabled and non-disabled workers and demand from employers. Many of these factors are not amenable to change by policy, but in this article we focus on a characteristic that can be modified, namely education. Education is now recognized as a key differentiating factor for both the prevalence of disability and employment of disabled people (Banks, Karjalainen, and Waters 2023). However, it is also a factor that has been neglected in most of the existing literature on disability and employment. While most studies that focus on disability wage or employment gaps include educational attainment as a control variable (e.g. Baldwin and Johnson 2000; Berthoud 2008; Jones and McVicar 2020), education 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, compared to non-disabled people.

The role of education in explaining the DEG can be attributed to the important link between human capital accumulation and labour market outcomes. 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. Where the expected wage is no greater than the reservation wage, which is partly determined by the availability of out-of-work benefits, one is unlikely to choose to participate (Kidd, Sloane, and Ferko 2000). In the UK, people are eligible for a higher level of out-of-work benefit subject to a Work Capability Assessment. As such, we would expect people with a work-limiting disability to have a higher reservation wage than those deemed fit for work. Moreover, less educated people choosing to participate are more likely to experience unemployment than more educated workers (Mincer 1991; Riddell and Song 2011).

Based on this evidence, we would expect employment rates to be higher among those with higher level qualifications. Disabled people on average have lower levels of education than non-disabled people (Latham 2012; Mann and Honeycutt 2014; Athanasou, Murphy, and Mpofu 2019; Mitra and Palmer 2023). They also largely compete in the

[3] https://www.gov.uk/government/news/government-hits-goal-to-see-a-million-more-disabled-people-in-work

same labour market as non-disabled people, which will adversely affect their employment prospects, and consequently the DEG.[4]

This article makes three important contributions to knowledge of disability and employment. First, we provide new evidence on the role that education can play in narrowing the DEG in the UK. To avoid the confounding effects of the coronavirus disease pandemic, we use data from the most recent prior year, 2019.[5] 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, preferences for paid work, and 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. Thirdly, 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, one standard approach to the Oaxaca–Blinder decomposition (Blinder 1973; Oaxaca 1973) is used unquestioningly, despite a number of developments in the literature, which show that there are many valid, and non-unique, ways to decompose an outcome gap, and that different methods imply different interpretations. We exploit these methodological developments in order to select the most appropriate decomposition to answer our specific research questions and construct meaningful counterfactual scenarios. At the same time, we stress that these decomposition methods do not provide a causal framework. The counterfactual scenarios presented are hypothetical and illustrative; as we discuss, they may overestimate or underestimate the true effects of educational equality on the DEG.

Our results show that a significant 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 could reduce the DEG by just over four percentage points, under the assumption that marginal employment returns to education are equal to average returns. This is consistent with previous studies, which find that higher levels of education mitigate the disadvantages experienced by disabled people. These findings hold 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, Nilsson, and Vikstrom 2015), the UK (Banks, Blundell, and Emmerson 2015; Jones and McVicar 2020) and the USA (Sevak et al. 2015; Venti and Wise 2015; McCauley 2020). Studies focussing on the DEG, as distinct from disabled people's employment only, are much rarer. However, Albinowski, Magda, and Rozszczypała (2024) find that the impact of education on the DEG varies substantially across countries in the European Union such that eliminating the education gap could reduce the DEG by as little as 2.7 per cent in Romania and as much as 13.9 per cent in Slovenia. This suggests that country-specific context is important for estimating the role of education in explaining the DEG.

Further decomposing the remaining 29 pp of the DEG reveals that 11 pp is explained by other non-modifiable characteristics while 18 pp (55 per cent of the DEG) is unexplained by observed characteristics. This is lower than a previous estimate of the unexplained component of the DEG in the UK (Jones 2006). However, there is considerable variation in

[4] However, UK government schemes do exist to help disabled people have better access to mainstream jobs. On the demand side, these include Access to Work, where employers can apply for public funds to pay for reasonable adjustments, and Disability Confident, a voluntary scheme accrediting employers for taking steps to improve disabled people's experience of work. On the supply side, the social welfare system provides support to disabled people not in work, both in terms of employability support and financial support if they are assessed as unfit for work.

[5] We have repeated the analysis for every year 2014–21 and obtain similar results.

estimates across studies focused on decomposing the DEG (Baldwin and Marcus 2007) and the disability gaps in labour force participation (Kidd, Sloane, and Ferko 2000), job loss (Mitra and Kruse 2016) and wages (Kidd, Sloane, and Ferko 2000; Thoursie 2004; Baldwin and Marcus 2007). We attribute this unexplained component to structural barriers; the gap that would remain if disabled people and non-disabled people had the same levels of education and other characteristics. These are defined as any factors that cause disabled people to behave or be treated differently in the labour market, such that their chances of employment are reduced despite having the requisite education and skills.

The underlying reasons for these structural barriers are subject to much debate about how to conceptualize 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. This suggests that lower employment levels could be due to latent productivity differences, which are not reflected in formal qualifications. Kidd, Sloane, and Ferko (2000) estimate that productivity related characteristics can explain about half of both the labour force participation gap and the wage gap in the UK, while Jones (2006) concludes that the unexplained component of the DEG is wholly due to productivity differences between disabled and non-disabled people because there is no gap when only non-work limited disabled people are included in the analysis. A similar conclusion is reached by Longhi, Nicoletti, and Platt (2012), in relation to the disability wage gap in the UK, insofar as productivity differences alone account for the wage gap. These results for the UK are largely replicated for Ireland (Gannon and Munley 2009) and other European countries (Malo and Pagan 2012), suggesting that productivity deficits explain much of the otherwise unexplained wage gap. This literature provides little evidence of discrimination.

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. As such, productivity differences may themselves be the result of structural factors. More generally, 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 (e.g. very physically demanding roles), but others can be overcome by workplace adjustments (e.g. 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 social model has been criticized 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 (World Health Organization 2001; Chandola and Rouxel 2021). 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 article, recognizing the particular status of disability in culture and legislation, but also differences in how institutions affect individuals.

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 value of people's skills and experience, making them less employable (Kroft, Lange, and Notowidigdo 2013). As such, it is difficult to dissociate preferences from discrimination and broader structural factors. However, we find that a large DEG exists even when we include only those expressing a preference for work, and 63 per cent of this gap is attributable to structural barriers.

Whilst the focus of much policy is about increasing the employment of disabled people, 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, occupations, industries, 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, there is a substantial disability wage gap in the UK (Kidd, Sloane, and Ferko 2000; Longhi, Nicoletti, and Platt 2012). In our sample, 34 per cent of employed disabled people work part-time compared to 23 per cent of employed non-disabled people. However, we do not take account of different types of work as this is beyond the scope of this article. 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.

2. Method

We start with a linear employment model[6] 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 K educational levels as their highest qualification. This is denoted by the vector $\mathbf{q}_i^D = (q_{i1}^D, \ldots, q_{iK}^D)$ where $q_{ik}^D \in (0,1)$ and $\sum_{k=1}^K q_{ik}^D = 1$. The vector $\boldsymbol{\beta}_q^D$ contains the coefficients pertaining to each qualification. Following Jann (2008), these coefficients are normalized 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 $\mathbf{x}_i^D$. As our research question focuses on the effects of educational investments on employment rates, $\mathbf{q}_i^D$is assumed to be the modifiable target for policy. The components of $\mathbf{x}_i^D$ are assumed to be fixed at least insofar as they would not be objects of policy intervention. Likewise, differentials in employment structure, as denoted by the relative size of the disabled and non-disabled coefficients, are also assumed to be fixed. However, as discussed below, there may be a role for policy to address these differentials.

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

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

where $\bar{y}^D$ denotes the sample mean of variable y_i^D and similarly for all right-hand side variables. Subtracting the equation for disabled people from the equation for non-disabled people gives the DEG:

[6] We are fitting our data to a linear probability model, rather than a non-linear specification, on the basis that our outcomes of interest (average employment rates for disabled and non-disabled people) are not close to 0 or 1 and hence marginal effects would be similar to those estimated by, for example, a probit model.

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

Following Oaxaca (1973) and Blinder (1973), Equation (3) can be expressed as a decomposition of the DEG into its explained and unexplained parts. To do this, an assumption must be made about the appropriate counterfactual employment structure (Oaxaca 1973), that is which set of coefficients should be used to value differences in the characteristics. There are multiple ways of decomposing the DEG and the results and interpretations are highly dependent upon the choice of counterfactual structure. This issue is referred to as the 'index problem' (Jann 2008; Fortin, Lemieux, and Firpo 2011), but the question of the appropriate counterfactual has received limited attention in the applied literature. Some studies of employment gaps use the non-disabled coefficients, either as a default choice (Mitra and Kruse 2016), or on the grounds that these would be the most likely to prevail if the employment structure were the same for disabled and non-disabled people (Baldwin and Marcus 2007). Others use an intermediate set of coefficients derived by pooling the disabled and non-disabled samples (Jones 2006), making the assumption that a non-discriminatory employment structure would lie between those currently experienced by disabled and non-disabled people respectively.

These choices can be criticized as arbitrary because either they rely on untestable assumptions about the nature of a counterfactual world, or there is no clear theoretical rationale for choosing one over the other.[7] We address this problem by linking the counterfactual structure more directly to the policy question of interest (Jones and Kelley 1984). Clarifying the goal of policy implies a particular counterfactual structure. As we initially want to model the effects of raising the education levels of disabled people to those of non-disabled people while keeping the employment structure of disabled people unchanged, it is appropriate to set $\widehat{\boldsymbol{\beta}}_q^1$ and $\widehat{\boldsymbol{\beta}}_x^1$ as the reference parameters. This generates the following decomposition:

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

Investing in the education of disabled people would affect only the first term of Equation (4). As more disabled people gain new qualifications, their probability of employment increases according to the employment returns for disabled people captured in $\widehat{\boldsymbol{\beta}}_q^1$. If sufficient investment were made such that disabled people had the same qualification levels on average as non-disabled people, then the first term in Equation (4) 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). It should be noted that, as is standard in decomposition frameworks, we implicitly assume homogenous returns to characteristics. In reality, they may differ across individuals, in which case $\widehat{\boldsymbol{\beta}}_q^1$ can be seen as the weighted average returns to education for disabled people.[8] We discuss below how our counterfactual predictions change if the marginal returns corresponding to an expansion of education diverge from the average returns. Further discussion of the index problem and its implications for our analysis is provided in the Supplementary Appendix.

Further methodological issues arise when breaking down the components of Equation (4); 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

7 Jones (2006) used a theoretically-based set of non-discriminatory coefficients developed by Neumark (1988) for the analysis of wage gaps. However, Neumark's method has subsequently attracted criticism (see discussion in Słoczyński, 2020).

8 In the context of a binary treatment variable in a regression with controls, Angrist and Pischke (2009) show that the OLS treatment coefficient is a weighted combination of the treatment effect within each cell defined by the controls.

the component due to differences in education (first term in Equation (4)), 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 category, 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 is largely arbitrary (Fortin, Lemieux, and Firpo 2011). Furthermore, we also wish to quantify the relative effects of all K qualifications that we consider in our analysis, rather than omitting a comparator qualification. Therefore, our strategy is to normalize the education coefficients, which amounts to taking the average of the detailed decompositions across all possible choices of omitted qualification.[9]

The second 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 problem. Instead, we adopt an approach developed by Horrace and Oaxaca (2001) and Fortin, Lemieux, and Firpo (2011). Given that $\sum_{k=1}^{K}\bar{q}_k^0=1$ where $\bar{q}_k^0$, $\widehat{\beta}_{q_k}^0$ and $\widehat{\beta}_{q_k}^1$ are the kth elements of $\bar{\mathbf{q}}^0$, $\widehat{\boldsymbol{\beta}}_q^0$ and $\widehat{\boldsymbol{\beta}}_q^1$ respectively, the structural component in Equation (4) can be expressed as:

$$\Delta_{q^0}^s=\left(\widehat{\beta}_0^0-\widehat{\beta}_0^1\right)+\bar{\mathbf{q}}^0\left(\widehat{\boldsymbol{\beta}}_q^0-\widehat{\boldsymbol{\beta}}_q^1\right)+\bar{\mathbf{x}}^0\left(\widehat{\boldsymbol{\beta}}_x^0-\widehat{\boldsymbol{\beta}}_x^1\right)=\sum\nolimits_{k=1}^{K}\bar{q}_k^0\Delta_{q_k^0}^s \tag{5}$$

where

$$\Delta_{q_k^0}^s=\left(\widehat{\beta}_0^0-\widehat{\beta}_0^1\right)+(\widehat{\beta}_{q_k}^0-\widehat{\beta}_{q_k}^1)+\bar{\mathbf{x}}^0\left(\widehat{\boldsymbol{\beta}}_x^0-\widehat{\boldsymbol{\beta}}_x^1\right) \tag{6}$$

The term $\Delta_{q_k^0}^s$ in Equation (5) 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 non-disabled people. It is made up of three parts: the differences in constants (the first term on the right-hand side of Equation (6)); the differences in returns to qualification k (second term); and the effects due to differences in returns to other characteristics (third term). The structural component of the overall DEG $\Delta_{q^0}^s$ is equal to the sum of the qualification-specific structural DEGs, weighted by the proportion of non-disabled people with each qualification as their highest, $\bar{q}_k^0$. Hence, the share of the structural component attributable to qualification k can be expressed as the kth term of the summation in Equation (5).

It is essential to interpret these shares correctly. The statistic $\Delta_{q_k^0}^s$ tells us by how much the DEG would reduce if there were no structural gap at all for people holding qualification k as their highest, not just the absence of a structural gap due to barriers specific to k (the second term on the right-hand side of Equation (6)). This is because $\Delta_{q_k^0}^s$ essentially

[9] Highest qualification is a categorical variable; we would usually expect one of the coefficients in $\boldsymbol{\beta}_q$ to be zero (the omitted category). Following Jann (2008), we normalize the highest qualification variable such that $\beta_{q_k}=\beta'_{q_k}-\frac{1}{K}\sum_{k=1}^{K}\beta'_{q_k}$ where β_{q_k} is the coefficient pertaining to the kth qualification in the normalized transformation and β'_{q_k} is the coefficient pertaining to the kth qualification, where one of the qualifications is omitted. It can be shown that $\sum_{k=1}^{K}\beta_{q_k}=0$. The normalized coefficient β_{q_k} can be interpreted as the amount by which the probability of employment would change if a typical individual moved from an 'average' qualification level to level k. All categorical, non-binary variables in $\mathbf{x}$ are also normalized.

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

incorporates all other structural barriers affecting the employment of disabled people indicated by the constant $(\widehat{\beta}_0^0 - \widehat{\beta}_0^1) + \bar{\mathbf{x}}^0(\widehat{\boldsymbol{\beta}}_x^0 - \widehat{\boldsymbol{\beta}}_x^1)$. 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. These relative contributions are invariant to the choice of omitted category, whereas the absolute contributions are not.

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

3. Data

Our data source is the Annual Population Survey (APS). This is an annually repeated cross-sectional dataset containing a representative sample of households and individuals from across the UK. In order to access a comprehensive set of variables, including detailed information about health conditions, we use the Secure Access version (Office for National Statistics, Social Survey Division 2022).[11] We use data from 2019, selected as the most recent pre-pandemic year. We retain individuals between the ages of twenty-five and sixty-four for the analysis; chosen to include people of working age, but who are likely to have completed their full-time education.

Our dependent variable y_i is employment status, based on the ILO definition of basic economic activity. It is a dummy variable equal to 1 if the individual is employed or self-employed and 0 if they are not employed. Our ‘treatment’ variable D_i is disability, defined according to the Equality Act (2010).[12] A person is deemed to be disabled ($D_i = 1$) if they report having any health problems or illnesses lasting 12 months or more and say that this reduces their ability to carry out day-to-day activities. They are otherwise classified as non-disabled ($D_i = 0$). We chose this measure to align with the UK’s legal definition of disability as a protected characteristic, which has in turn been adopted by the government to define and monitor the DEG. Under this definition, individuals can effectively self-identify as disabled, which arguably is not an objective measure of ‘true’ disability. A person’s employment status may influence this self-reporting to the extent that the disability measure can be deemed endogenous (Kreider 1999).[13] However, there is evidence to suggest that self-reported measures of disability obtained from anonymous non-governmental surveys are unbiased (Benítez-Silva et al. 2004).

The disabled population can be classified further into whether their condition is related to physical health, mental health, or both. Supplementary Appendix Table A4 shows the different health conditions covered in the APS survey and how they are categorized. Many disabled people have more than one health condition and hence some people in our sample have both physical and mental health conditions.[14] We also classify the disabled population into severity of impairment; 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’.

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

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

[13] We do not adopt the definition of ‘work-limiting disability’ as used in several other papers in the DEG literature as this does not align with the legal definition of disability in the UK. Moreover, in a labour market context, it is likely to suffer even more from endogeneity than the ‘day-to-day activities’ definition that we use.

[14] 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 the main analysis but are removed from the analysis relating specifically to physical and mental health conditions.

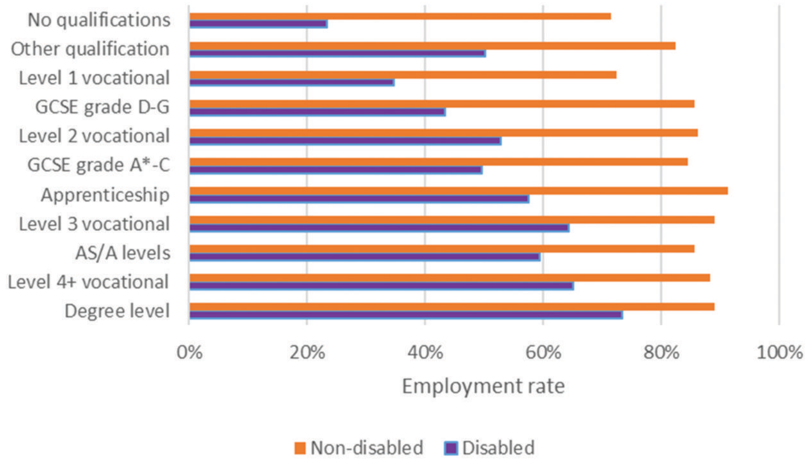

Figure 1. Employment rates by highest qualification, 2019.
Source: Annual Population Survey.

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. Evidence from the returns to education literature in the UK suggests that returns vary according to not only the level of the qualification but also whether it is academic or vocational in nature (McIntosh 2006).[15] In the UK, qualifications are classified into levels with vocational and academic qualifications situated at each level. Supplementary Appendix Table A2 shows how we classify each of the 84 qualifications identified in the APS into one of eleven mutually exclusive highest qualification levels (McIntosh and Morris 2021). We also control for a number of other characteristics to make up $\mathbf{x}_i$ and these are detailed in Supplementary Appendix Table A7.

4. Results

4.1 Overall DEG

The overall DEG in 2019 was 33 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 Fig. 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 16 pp among those educated to degree level to 48 pp among those with no qualifications. While non-disabled people with no qualifications have an employment rate just 17 pp below non-disabled people with a degree, the gap between disabled people with no qualifications and disabled people with a degree is 50 pp. 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.

The means of each highest qualification among disabled and non-disabled people, and the coefficients from the individual equations where highest qualification is normalized, as per Equation (2), are shown in Table 1. For comparison, the means and coefficients of all

[15] While academic qualifications offer comprehensive subject knowledge and generic skills, vocational qualifications emphasize technical and procedural knowledge and skills, which are often relevant to specific occupational roles (Espinoza and Speckesser 2019).

Table 1. Means and estimated coefficients of highest qualification.

Highest qualification	Non-disabled people		Disabled people	
	Mean $\bar{q}_k^0$	Coefficient $\widehat{\beta}_{q_k}^0$	Mean $\bar{q}_k^1$	Coefficient $\widehat{\beta}_{q_k}^1$
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

Notes: $N = 134{,}103$. All other control variables were included but not shown. Standard errors in brackets.
Source: Annual Population Survey.
* $P < .05$.
** $P < .01$.

other variables in the model, (excluding local areas) are shown in Supplementary Appendix Table A5. This shows that there are large differences in the qualification levels of disabled and non-disabled people. Nearly two-fifths (39 per cent) of non-disabled people are educated to degree level or higher compared to less than a quarter (24 per cent) of disabled people. Disabled people are nearly three times as likely not to have any qualifications (17 per cent, compared to 6 per cent 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 two equations. For non-disabled people, holding a degree increases the probability of employment by only 3.5 pp 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 13.3 pp 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 3.4 pp lower employment for holding GCSEs at grade A*–C as their highest and 6.2 pp 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 18.5 pp lower employment rate for disabled people but only 8.4 pp for non-disabled people.

Table 2. Decomposition of overall DEG.

DEG	0.3318**
	(0.0031)
Degree	0.0200**
	(0.0010)
Level 4+ vocational	0.0004**
	(0.0001)
AS/A levels	0.0004**
	(0.0001)
Level 3 vocational	−0.0003
	(0.0002)
Apprenticeship	−0.0000
	(0.0000)
GCSEs grade A*–C	0.0006**
	(0.0001)
Level 2 vocational	−0.0005*
	(0.0002)
GCSEs grade D–G	0.0006**
	(0.0002)
Level 1 vocational	0.0004**
	(0.0001)
Other	−0.0001
	(0.0001)
No qualifications	0.0190**
	(0.0008)
Sum of education factors	0.0406**
	(0.0013)
Other characteristics	0.1073**
	(0.0023)
Structural component	0.1839**
	(0.0034)
Education (%)	12
Other characteristics (%)	33
Structural (%)	55
N	134,103

Notes: Decomposition based on Equation (4). Standard errors in brackets.
Source: Annual Population Survey.
* $P < .05$.
** $P < .01$.

Table 2 shows the decomposition of the DEG into characteristics and structural components as per Equation (4). The results including all covariates are reported in Supplementary Appendix Table A6. Note that the sum of the characteristics component and the structural component adds up to the DEG.

The results show that differences in educational attainment between disabled and non-disabled people explain a gap of 4.1 pp, of which 2.0 pp is explained by fewer disabled people having degrees and 1.9 pp is explained by more disabled people having no qualifications. This accounts for about 12 per cent of the total DEG of 33.2 pp. Assuming an overall policy objective of halving the DEG to 16.6 pp, a complete elimination of the education gap would account for 24 per cent of this reduction. We do not suggest that this effect is causal as, due to unobserved factors, disabled people newly acquiring qualifications may not have the same rates of employment as disabled people already holding those same qualifications. We come back to the issue of heterogeneous returns in the Conclusion.

A much larger gap of 10.7 pp (33 per cent of the total DEG) is explained by other differences in characteristics between the two groups. While some of these differences (e.g.

Table 3. Attribution of the structural component to qualification levels.

	Structural component $\Delta^s_{q^0_k}$	Attribution (pp) $\bar{q}^0_k \Delta^s_{q^0_k}$	Attribution (%) $\bar{q}^0_k \Delta^s_{q^0_k} / \Delta^s_{q^0}$
Degree	0.123** (0.005)	0.048** (0.002)	26
Level 4+ vocational	0.171** (0.011)	0.013** (0.001)	7
AS/A levels	0.189** (0.011)	0.014** (0.001)	7
Level 3 vocational	0.162** (0.009)	0.016** (0.001)	8
Apprenticeship	0.241** (0.015)	0.008** (0.001)	4
GCSEs grade A*–C	0.253** (0.008)	0.036** (0.001)	19
Level 2 vocational	0.223** (0.012)	0.011** (0.001)	6
GCSEs grade D–G	0.287** (0.016)	0.006** (0.001)	3
Level 1 vocational	0.250** (0.035)	0.001** (0.000)	1
Other	0.214** (0.013)	0.012** (0.001)	6
No qualifications	0.322** (0.009)	0.020** (0.001)	11
Total	–	0.184 (0.003)	100

Notes: $N = 134{,}103$. Bootstrapped standard errors in brackets.
Source: Annual Population Survey.
* $P < .05$.
** $P < .01$.

family structure) might be amenable to policy interventions, our focus here is on education as the primary modifiable characteristic related to employment. The remaining gap of 18.4 pp (55 per cent of the DEG) is attributable to structural factors. This can be interpreted as the DEG that would persist even if disabled people had the same level of education and the same characteristics on average as non-disabled people.

Table 3 shows how the structural component of the DEG can be attributed to each qualification level, following Equations (5) and (6). Looking first at the structural components themselves for each qualification, it is clear that wider structural gaps exist for people with lower levels of educational attainment, ranging from 32.2 pp for people with no qualifications to 12.3 pp for people with degrees. However, once these structural components are weighted by the average qualification levels of non-disabled people (Equation 5), we see that the structural gap among people with a degree accounts for over a quarter (26 per cent) of the overall structural gap. The estimates in Table 3 reflect the hypothetical world following the policy of raising the average education levels of disabled people to be the same as those of non-disabled people. In such a scenario, almost two-fifths (39 per cent) of disabled people would have a degree. Therefore, due to the sheer number of disabled people holding a degree relative to other qualifications, addressing structural barriers affecting this group alone would have the largest effect on reducing the DEG. A further 19 per cent of the structural gap is attributable to those with GCSEs grade A*–C as their highest qualification and 11 per cent is attributable to those with no qualifications.

Table 4. Decomposition of DEGs by sex and age.

	Female	Male	Age 25–34	Age 35–49	Age 50–64
DEG	0.2944**	0.3682**	0.2765**	0.3024**	0.3421**
	(0.0041)	(0.0047)	(0.0077)	(0.0053)	(0.0045)
Degree	0.0248**	0.0140**	0.0308**	0.0262**	0.0084**
	(0.0015)	(0.0015)	(0.0028)	(0.0019)	(0.0011)
Level 4+ vocational	−0.0000	0.0008**	−0.0005	0.0004	0.0006*
	(0.0002)	(0.0002)	(0.0006)	(0.0004)	(0.0003)
AS/A levels	0.0002	0.0006*	−0.0000	0.0003	0.0001
	(0.0001)	(0.0002)	(0.0003)	(0.0002)	(0.0002)
Level 3 vocational	−0.0005	−0.0001	−0.0011	−0.0018**	0.0005*
	(0.0003)	(0.0002)	(0.0006)	(0.0004)	(0.0002)
Apprenticeship	−0.0001	−0.0001	0.0000	0.0000	0.0000
	(0.0001)	(0.0002)	(0.0002)	(0.0000)	(0.0000)
GCSEs grade A*–C	0.0011**	0.0001	0.0021**	0.0006	−0.0004*
	(0.0003)	(0.0001)	(0.0007)	(0.0004)	(0.0002)
Level 2 vocational	−0.0005	−0.0004	0.0002	−0.0001	−0.0007**
	(0.0003)	(0.0002)	(0.0008)	(0.0005)	(0.0002)
GCSEs grade D–G	0.0011**	0.0001	0.0013*	0.0007**	0.0003*
	(0.0002)	(0.0002)	(0.0005)	(0.0003)	(0.0001)
Level 1 vocational	0.0004**	0.0004*	0.0008	0.0008**	0.0001
	(0.0002)	(0.0002)	(0.0004)	(0.0003)	(0.0001)
Other	−0.0000	−0.0001	−0.0011*	−0.0000	−0.0003
	(0.0001)	(0.0001)	(0.0005)	(0.0001)	(0.0002)
No qualifications	0.0193**	0.0188**	0.0180**	0.0164**	0.0186**
	(0.0011)	(0.0013)	(0.0019)	(0.0013)	(0.0013)
Sum of education factors	0.0458**	0.0341**	0.0506**	0.0436**	0.0272**
	(0.0019)	(0.0020)	(0.0037)	(0.0024)	(0.0017)
Other characteristics	0.0728**	0.1392**	0.0668**	0.1067**	0.0883**
	(0.0029)	(0.0038)	(0.0059)	(0.0042)	(0.0030)
Structural component	0.1758**	0.1949**	0.1592**	0.1521**	0.2266**
	(0.0044)	(0.0051)	(0.0083)	(0.0058)	(0.0048)
Education (%)	16	9	18	14	8
Other characteristics (%)	24	38	24	35	26
Structural (%)	60	53	58	50	66
N	71,308	62,795	28,810	49,924	55,369

Notes: Standard errors in brackets.
Source: Annual Population Survey.
* $P < .05$.
** $P < .01$.

4.2 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, and the DEGs for each age group. Overall, the gap is wider for males (36.8 pp) than females (29.4 pp). 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. Achieving educational parity is predicted to have a greater effect on the female DEG (16 per cent) than the male DEG (9 per cent). For both sexes, reducing the number of disabled people with no qualifications and increasing the number of disabled people with degrees is predicted to have the most impact. However, improving the qualification levels of those in the middle of the educational distribution is also predicted to have an impact particularly for females.

It is also possible that the relationship between employment and education may vary according to age. Table 5 shows that people over the age of fifty are much less likely than

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

Source: Annual Population Survey.

younger people to have a degree. They are also more likely to have no qualifications. The last three columns of Table 4 show that the DEG is larger for older people, rising from 28 pp among 25–34 year olds to 34 pp among 50–64 year olds. However, education also explains more of the DEG for younger people. Achieving parity of education would reduce the DEG by 5.1 pp (18 per cent) for 25–34 year olds, a figure very close to the 18.7 per cent estimate of Albinowski, Magda, and Rozszczypała (2024) for EU countries on average. However, their estimates vary greatly across countries and exclude people without primary education.[16] In contrast, the effect is just 2.7 pp (8 per cent) for 50–64 year olds. For the youngest age group, achieving parity in the proportion of people with a degree is predicted to have the most effect (3.1 pp) but the effect would be negligible (0.8 pp) 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.

4.3 DEGs by health conditions

We now turn to the separate DEGs for people with mental and physical health conditions and with 'more severe' and 'less severe' impairments. As shown in Table 6, the mental health DEG (46.3 pp) is higher than that for physical health (34.2 pp). Educational inequalities account for a similar proportion of the mental health and physical health DEGs (13 per cent and 12 per cent, respectively), suggesting that education is equally important for people with mental health and physical health conditions.

As one would expect, disabled people with a more severe impairment have much lower employment rates than those with a less severe impairment. Hence there is a big difference in the DEGs (57.1 pp compared to 13.9 pp). Achieving education parity is predicted to disproportionately help those with more severe impairments, reducing the more severe DEG by 6.2 pp and the less severe by 1.1 pp. In both cases, most of this reduction is achieved by decreasing the number of disabled people with no qualifications and increasing the number of disabled people with degrees.

[16] In addition, the methodology used in Albinowski, Magda, and Rozszczypała (2024) differs from the Blinder–Oaxaca approach we use in this article. First, they employ a Probit model so their decomposition results are obtained using average marginal effects. Secondly, they modify the country-specific marginal effects of education using average EU marginal effects from a separate dataset. In supplemental analysis, they also provide the Blinder–Oaxaca decomposition results, which are larger (23.6 per cent) but these still exclude individuals without primary education. Given the importance of individuals with 'no qualifications' in our analysis, we expect that the Albinowski, Magda, and Rozszczypała (2024) results are a conservative estimate of the role of education in explaining the DEG in EU countries.

Table 6. Decomposition of DEG by mental and physical health conditions and 'more severe' and 'less severe' impairments.

	Mental health	Physical health	More severe impairment	Less severe impairment
DEG	0.4630**	0.3418**	0.5713**	0.1391**
	(0.0046)	(0.0034)	(0.0041)	(0.0037)
Degree	0.0323**	0.0205**	0.0330**	0.0070**
	(0.0019)	(0.0013)	(0.0023)	(0.0007)
Level 4+ vocational	0.0015**	0.0003	0.0011**	−0.0002
	(0.0003)	(0.0001)	(0.0003)	(0.0001)
AS/A levels	0.0004*	0.0004*	0.0002	0.0000
	(0.0002)	(0.0002)	(0.0003)	(0.0000)
Level 3 vocational	−0.0001	−0.0003	0.0005*	−0.0009**
	(0.0003)	(0.0002)	(0.0002)	(0.0002)
Apprenticeship	−0.0000	−0.0000	0.0000	−0.0001
	(0.0001)	(0.0001)	(0.0000)	(0.0001)
GCSEs grade A*–C	0.0011**	0.0006**	0.0012**	0.0002
	(0.0003)	(0.0002)	(0.0003)	(0.0001)
Level 2 vocational	0.0005	−0.0005*	−0.0005	−0.0002
	(0.0004)	(0.0002)	(0.0003)	(0.0002)
GCSEs grade D–G	0.0013**	0.0005**	0.0010**	0.0002
	(0.0003)	(0.0002)	(0.0003)	(0.0001)
Level 1 vocational	0.0003	0.0004**	0.0003	0.0003**
	(0.0002)	(0.0001)	(0.0002)	(0.0001)
Other	−0.0001	−0.0002	0.0002	0.0001
	(0.0001)	(0.0001)	(0.0002)	(0.0001)
No qualifications	0.0235**	0.0191**	0.0248**	0.0049**
	(0.0015)	(0.0010)	(0.0016)	(0.0005)
Sum of education factors	0.0606**	0.0406**	0.0619**	0.0114**
	(0.0025)	(0.0016)	(0.0028)	(0.0009)
Other characteristics	0.1303**	0.1144**	0.1510**	0.0433**
	(0.0045)	(0.0028)	(0.0045)	(0.0022)
Structural component	0.2721**	0.1868**	0.3584**	0.0844**
	(0.0056)	(0.0039)	(0.0057)	(0.0038)
Education (%)	13	12	11	8
Other characteristics (%)	28	33	26	32
Structural (%)	59	55	63	60
N	116,522	127,759	117,477	120,722

Notes: Standard errors in brackets.
Source: Annual Population Survey.
* $P < .05$.
** $P < .01$.

4.4 DEGs by labour market preferences and attachment

Individual preferences potentially have an important role to play in the DEG; a factor that is rarely, if ever, explored in the existing 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 article, 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.[17] This exclusion is done with caution because 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

[17] 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. Those answering 'yes' are also assumed to have a preference for work while those answering 'no' are removed from the sample.

Table 7. Decomposition of DEGs based on different measures of labour market attachment.

	Preference for work	Strongly attached	Weakly attached
DEG	0.1661**	0.0502**	0.1484**
	(0.0030)	(0.0021)	(0.0031)
Degree	0.0091**	0.0014**	0.0058**
	(0.0008)	(0.0004)	(0.0007)
Level 4+ vocational	−0.0001	−0.0001	−0.0002
	(0.0001)	(0.0001)	(0.0001)
AS/A levels	0.0002*	0.0001	0.0001
	(0.0001)	(0.0001)	(0.0001)
Level 3 vocational	−0.0010**	−0.0002	−0.0006**
	(0.0002)	(0.0001)	(0.0002)
Apprenticeship	−0.0000	−0.0000	−0.0000
	(0.0001)	(0.0000)	(0.0001)
GCSEs grade A*–C	0.0000	0.0000	0.0002
	(0.0001)	(0.0000)	(0.0001)
Level 2 vocational	−0.0002	0.0000	0.0003
	(0.0002)	(0.0002)	(0.0003)
GCSEs grade D–G	0.0005**	0.0000	0.0001
	(0.0001)	(0.0001)	(0.0001)
Level 1 vocational	0.0004**	0.0000	0.0001
	(0.0001)	(0.0001)	(0.0001)
Other	−0.0001	−0.0000	−0.0001
	(0.0001)	(0.0000)	(0.0001)
No qualifications	0.0040**	0.0010**	0.0027**
	(0.0004)	(0.0002)	(0.0004)
Sum of education factors	0.0129**	0.0021**	0.0084**
	(0.0009)	(0.0005)	(0.0008)
Other characteristics	0.0487**	0.0110**	0.0383**
	(0.0019)	(0.0012)	(0.0018)
Structural component	0.1046**	0.0371**	0.1016**
	(0.0032)	(0.0024)	(0.0033)
Education (%)	8	4	6
Other characteristics (%)	29	22	26
Structural (%)	63	74	68
N	113,762	109,631	118,023

Notes: Standard errors in brackets.
Source: Annual Population Survey.
* $P<.05$.
** $P<.01$.

experiencing ‘hidden unemployment’ (Beatty et al. 2022). Nevertheless, although the preference-based DEG is smaller than the overall DEG, a gap still exists (16.6 pp), demonstrating that, even among those who say they want to work, disabled people are still significantly less likely to be employed.

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 5.0 pp. If we remove everyone who left their last job more than five years ago or have never worked, the DEG is 14.8 pp. We define these DEGs as the ‘strongly attached’ and ‘weakly attached’ DEGs respectively.

We decompose these different DEGs in Table 7. This is informative for a policy that seeks only to improve the employment prospects of disabled people who are close to the labour market.

The table shows that investing in education is predicted to have a relatively small effect on the preference-based DEG (1.3 pp or 8 per cent). 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 (0.2 pp or 4 per cent) and the 'weakly attached' DEG (0.8 pp or 6 per cent), although other characteristics do explain a larger share of the gap.

5. Discussion and conclusion

This article provides new insights on the importance of education to the DEG in the UK. Our results suggest that a significant proportion of the DEG can be explained by inequalities in educational attainment between disabled and non-disabled people. However, there is also a large unexplained component, highlighting the need also to tackle structural inequalities in the labour market.

We show that if disabled people could achieve qualification levels equal to those of non-disabled people, this may by itself reduce the gap by up to 12 per cent, an effect that would be greater for females than males, and greater for younger people than older people. This would be equivalent to 24 per cent of a target to halve the DEG. It is important to note that such impacts would be achieved only if the marginal employment returns to education were equal to the average returns, such that newly qualified individuals have the same probability of employment given their qualifications as individuals who already have these qualifications. However, it is not clear cut *a priori* to say that marginal returns will always be lower than average returns. One might expect marginal returns to be lower than average returns due to self-selection into education.[18] In this case, the true effect of eliminating educational inequalities would be to reduce the DEG by less than 12 per cent. However, there is evidence to suggest the marginal returns to education might be larger than the average returns for disabled individuals. Baumberg (2015) argues that education provides access to better quality jobs that allow enough flexibility to work around impairments. If disabled individuals with more severe impairments self-select out of higher education based on the severity of their disability, then this group would potentially benefit even more from obtaining higher qualifications relative to individuals with less severe conditions who self-select into higher education. This is because the former group face higher barriers to employment so would have more to gain from having access to more flexible jobs. Conversely, disabled individuals who self-select into higher education face relatively lower barriers to employment so they are more likely to have positive employment outcomes regardless of their qualification level. In this case, equalizing education could reduce the DEG by more than 12 per cent.

While other differences in characteristics between disabled and non-disabled people explain some of the remaining gap, we estimate that about 55 per cent of the DEG is unexplained. 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 article 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

[18] This would be consistent with evidence from the wage returns literature that the marginal returns to education are less than the average returns (Carneiro, Lokshin, and Umapathi 2017).

supply, the effect would be to halve the DEG from 33 pp to 17 pp. 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. However, our analysis suggests that removing educational inequalities would have a smaller effect on this preference-based 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 the difference in coefficients is particularly large for people with no qualifications, 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.

First, as disabled people tend to face more barriers in education, those who do attain a good education may have other qualities, that are 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 low educational attainment is a marker for severity or early 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, suggesting that heterogeneity in the severity of impairment may be explaining some of this gradient. Although we cannot observe the timing of onset, we find minimal difference between mental health disability and physical health disability in the extent to which education explains the DEG. Given that the onset of physical health conditions tend to occur later in life than mental health conditions on average (Banks, Karjalainen, and Waters 2023), we would expect to see some difference if it mattered whether the onset of disability occurs before or after completion of full time education. This relates to mixed evidence in the literature on how the timing of disability onset affects returns to education (Wilkins 2004; Hollenbeck and Kimmel 2008; Henderson, Houtenville, and Wang 2017).

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 (Cutler, Landrum, and Stewart 2006; Baumberg 2015). In fact, there is evidence to show that disabled people tend to be over-qualified for the work that they do (Jones et al. 2014).

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. 2024). 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 years (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. The investment required to achieve educational equity should not be underestimated. It is not sufficient simply to expand the supply of education places to create opportunities for disabled people to study for qualifications. Many disabled students at the margins (including individuals with mental health conditions or more severe impairments) will need additional support to achieve these qualifications, relative to the support required by existing student caseloads.

However, in a counterfactual world where such individuals do achieve these qualifications, there is evidence to suggest that the effect on their employment, while uncertain, may be significant. The possession of good qualifications can help overcome barriers to employment (Baumberg 2015) or reduce statistical discrimination (Dickerson et al. 2024). It should of course be noted that, particularly in labour markets with high unemployment, newly employed disabled people may displace non-disabled people, although paradoxically this would reduce the DEG still further. However, such general equilibrium effects seem unlikely to be a significant problem in the UK labour market, at least in the long run.

Notwithstanding these potential gains to increases in qualifications, a bigger challenge 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.

Supplementary material

Supplementary material is available at the *Oxford Economic Papers Journal* online. This includes the Online Appendix and a Stata do-file to allow for replication of our results. This article uses data from the Annual Population Survey, owned by the Office for National Statistics and accessed through the UK Data Service Secure Lab. As such, the data are confidential and cannot be shared. However, researchers can apply to access the data through the UK Data Service Secure Lab: https://ukdataservice.ac.uk/help/secure-lab/.

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