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The UK Disability Discrimination Act 2005: Consequences for the education and employment of older children

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ABSTRACT

We investigate the impact of the 2005 UK Disability Discrimination Act on the educational and employment outcomes for older children with disabilities, using data from the UK Labour Force Surveys. The Act established new legal requirements on employers and qualification awarding bodies to accommodate individuals with disabilities. Furthermore, prior to 2013 children in England and Wales could leave education at age 16, providing a unique opportunity to analyse the 2005 Act's influence on their educational and employment outcomes. Compared to children without disabilities, we found the 2005 Act reduced the likelihood of continuing in education and increased the likelihood of entering the labour market (employed or unemployed) for children meeting both the 1995 Disability Discrimination Act definition of disability and who were reported as work-limited. We also 'decompose' average outcomes between children's groups, identifying effects attributable to observable characteristics, discrimination, and unobservable health-related productivity gaps.

1. Introduction

Amongst the several disability acts introduced from 1995 to 2010, the Disability Discrimination Act of 2005 (DDA'2005) made substantial legislative amendments in relation to employment and education. The act made it illegal to publish discriminatory job advertisements and required employers to make reasonable provisions for job applicants and employees with disabilities. Furthermore, it prohibited qualifications-awarding bodies from discriminating against disabled persons and required them to make reasonable adjustments for access and provision, but not for competence standards. Given the importance of these amendments to older children seeking qualifications and entering the labour market, we compare the impact of the DDA'2005 on the educational and employment outcomes for 16- and 17-year-olds, with and without disabilities in England and Wales.

We analyse children aged 16 and 17 on August 31st of each year because, between 1973 and 2013, they could choose to end their full-time education after their 16th birthday by not attending the final two years of secondary education. We limit the analysis to England and Wales because we are better able to identify in which academic year a child was enroled given, unlike other parts of the UK, only one annual cut-off date was used to determine entry into education. After 2013, some degree of compulsory education to age 18 was introduced in England and thereafter to other parts of the UK.

We use the UK Labour Force Surveys (LFS) to access data on sampled 16- and 17-year-old children, as it is otherwise difficult to obtain such detailed personal information on minors, including linked data on parents or guardians. We restrict our study to the 1998–2013 LFSs because questions related to disabilities, education and work remained unchanged over this period. We chose not to analyse 18- and 19-year-olds as many leave the parental home and therefore tend to be under-sampled in the LFS. Furthermore, data on their parents and guardians are absent if they have left the parental home.

Though we present our analysis as if the decision was made by the child, we do not preclude that it was in part, or wholly, determined by parents or guardians. Our first hypotheses is that the DDA'2005 legislation had no impact on the choices made by children without disabilities. Our second hypothesis is that the legislation might have encouraged or discouraged children with disabilities to remain in education. On the one hand, better lifetime employment prospects might

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have encouraged children with disabilities to invest more heavily in education to increase potential lifetime earnings. On the other hand, it might be that prior to the DDA'2005 children with disabilities had over-invested in education to overcome anticipated discrimination or disability-specific labour market costs.

We remain agnostic as to the 'inefficiency' of over-investment in education because there are many inefficiencies that lead to under-investment and it is hard to determine the net effect, or how close the actual level of education is to an efficient level. We return to this issue in the Literature Section. One way we can check that our results are not spurious is to verify that the DDA'2005 did not affect the educational and employment choices of children without disabilities. Furthermore, because the total number of children without disabilities far exceeds that of children with disabilities, we do not expect to see spillover effects from the smaller group. The effect of any legislation can take time, we therefore carry out our analysis on data that span several years before and after Royal Assent on 7 April 2005, and the eighteen months it took to implement the DDA'2005.

In SubSection 5.1 we report multinomial Logit model estimates for whether each child is: a student, in employment, unemployed or inactive in the labour market. Given the limited nature of the dependant variable, this is the closest we can get to a difference-in-difference analysis while maintaining some empirical rigour and return to this issue in Section 4, including the validity of difference-in-difference analysis when applied to limited depended variables. The validity of our analysis is supported by statistically significant effects of the DDA'2005 for children who are both with disabilities and work-limited (Table 4). Throughout we use multivariate analyses where a range of individual and parental socio-economic characteristics are included. This also allows for the DDA'2005 effects to vary by gender. In SubSection 5.2, we analyse how the realized outcomes for children with declared 'disabilities and work limitations' (LFS terminology) differ from those in large control group of 'not disabled' children. We use Fairlie-Blinder-Oaxaca decompositions (Blinder, 1973; Fairlie, 1999, 2005; Oaxaca, 1973) to carry out this final part of the analysis for two reasons. The first is that Fairlie-Blinder-Oaxaca decompositions provide an explicit comparison between groups. The second reason is that Fairlie-Blinder-Oaxaca decompositions allow one to decompose group differences between 'endowment effects' (sometimes called explained or characteristics effects) and 'coefficient effects' (sometimes called unexplained, discrimination or behavioural effects). In other words, the difference between children with and without disabilities is due both to different circumstances and different responses to the same circumstances. These results are supplemented by a DeLeire-Jones analysis (DeLeire, 2001; Jones, 2006) where the coefficient effects from pairs of Fairlie-Blinder-Oaxaca decompositions are used to estimate discrimination and health-related productivity effects.

The reminder of the paper is organised as follows. Section 2 provides a short literature survey on over-education and the impact of disability on labour market outcomes. Section 3 presents details of LFS data and some simple summary statistics. Section 4 presents the modelling strategy and methodology. Section 5 presents and discusses the results. A final section concludes. Any errors are our own.

2. Literature

The relation between health status and the decision to stay in education, enter the labour market, or become labour market inactive is often studied by economists by framing it within the human capital model developed by Becker (1967) and Ben-Porath (1967). According to this theory, individuals motivated by higher future earnings increase their labour market productivity by investing in schooling early in their life. The optimal level of schooling varies amongst individuals depending on their health status as this affects the cost of learning, life expectancy, labour market barriers to entry, and opportunity costs. Within this framework, numerous empirical studies have explored the impact of disability onset in adults on their labour market outcomes, and find that health has a statistically significant impact on the level of schooling. See Eide (2011) for a review and Soares (2006) for country-specific evidence. Disability in adulthood has also been found to affect the decision to enter or exit the labour market. For recent contributions see Brown, Roberts and Taylor (2010) and Jones and McVicar (2020) for Britain, as well as Jolly and Wagner (2023) for the USA.

Though focused on schoolchildren, our work is closely aligned to studies that have examined the impact of legislative changes in disability rights on the adult labour market, including Kim and Rhee (2018) for the USA, and Garcia-Mandicó, García-Gómez, Gielen and O'Donnell (2020) for the Netherlands. While legislative changes may be intended to boost employment opportunities for people with disabilities, economic theory suggests their impact is ambiguous. On the one hand, as discussed extensively by Matsui (2019), anti-discrimination laws might dictate easier access to a wide range of jobs for workers with disabilities. On the other hand, these laws could render the employment of individuals with disabilities costlier to employers due to the required reasonable adjustments, and possible litigation risks which may lead to lower employment (Armour et al., 2018). The existing empirical evidence is indeed mixed and has focused primarily on the US context. Some authors have found no effects or positive employment effects of new labour legislation aimed at people with disabilities (see Armour et al. (2018), Hotchkiss (2004), Kruse and Schur (2003), and Button (2018)), while others have found negative employment effects (see DeLeire (2000) and Acemoglu and Angrist (2001)).

Fewer authors have focused on the effect of new legislation on the transition of older children with disabilities into adulthood, in terms of either completion of school or entering the labour market. Dean, Pepper, Schmidt and Stern (2019) offer notable research on this area, evaluating the effectiveness of the US's Virginia State school-to-work vocational evaluation programme. They find evidence of a statistically significant and positive long-term effect on labour-market outcomes for those who undertake the vocational rehabilitation services.

We believe our study is the first to examine the impact of a legislative change in disability rights on older children's decisions to either continue in education or enter the labour market. Our analysis centres on the timing of the UK Disability Discrimination Act of 2005 (DDA'2005), which replaced and superseded the DDA'1995. The new legislation expanded the responsibilities of qualifications-awarding bodies and employers to make reasonable adjustments for existing and prospective employees with disabilities.

Our view is that if, prior to the DDA'2005, children with disabilities had been over-investing in education in order to overcome the disability hurdle, implementation of the act would remove some of the motives for this over-education. In the context of the existing literature, over-investment in education to counteract discrimination is inefficient insofar as it is driven by a market failure where potential employers are pre-judging candidates on their disabilities (e.g. Lang & Manove, 2011). The literature contains numerous examples of over- and under-education that are driven by other forms of market failure but we are not aware of any of these papers that focus specifically on the issue of over- and under-education amongst children with disabilities. The literature on over-education (e.g. and De Grip, 1989, Tsang & Levin, 1985, 1989) typically focuses on various short-run informational asymmetries between employers and job candidates. For example, if qualifications are taken as a signal of innate ability, children not under immediate financial pressure to become employed might over-invest in education to reap benefits later in life.

The literature on under-education is typically based on the view that children might have excessively high (hyperbolic) discount rates (Babcock, 2004, 2009, and Bettinger & Slonim, 2007). It is, therefore, difficult to say with any certainty if an anti-discrimination policy brings children with disabilities closer or further from an 'efficient' education investment decision when there are over- and under-education forces at play. Perhaps all one can venture to say is that the reduction of any discriminatory practice is in itself desirable.

Other studies have utilised UK LFS data to explore aspects of disability and labour market participation amongst adults. For instance, Jones (2022) investigated the impact of COVID-19 on the labour market outcomes of disabled adults. Banks, Blundell, Bozio and Emmerson (2011) studied how the DDA'1995 and resulting changes to health-related benefits were associated with later trends in adult labour market participation. Our work is the first to conduct a large-scale empirical study, using UK LFS data, to assess the impact of new national-level disability policy on older children's decisions to remain in education or participate in the labour market, thus filling a notable gap in the literature.

3. Data

In this section we discuss the data, how we select the sub-sample of older children aged 16–17, present summary statistics and illustrate some key trends.

3.1. Survey instrument

We use LFS data because it offers information on older children that we cannot obtain from other sources. Most importantly, the LFS maintained a consistent set of unchanging questions on disability from 1997 to 2013. The design of the LFS questions was based on definitions of disability outlined in the DDA'1995. Our analysis focuses on the LFS 'derived' variable DISCURR. This variable is derived by the LFS using other survey variables and it captures four possible states for each respondent:

"DISCURR - Current disability

(1) Both DDA (current disability) and work-limiting disabled
(2) DDA disabled (current disability) only
(3) Work-limiting disabled only
(4) Not disabled"

where DDA identities if a person has disabilities according to the DDA'1995. According to the Labour Force Survey User Guide (2012 vol.3, p.252) "DDA disabled (current disability) includes those who have a long-term disability which substantially limits their day-to-day activities. Work-limiting disabled includes those who have a long-term disability which affects the kind or amount of work they might do." We are therefore able to focus our analysis on whether the work-related emphasis of the DDA'2005 legislation had a specific effect on children who were "(1) Both DDA (current disability) and work-limiting disabled". We are also able to use the "(4) Not disabled" as a reference group that should not have been affected by the legislation. While mindful of the vagaries of self-reported data, we hypothesise that DISCURR groups (2) and (3) are less likely to demonstrate a substantial effect from the DDA'2005. Those in groups (2) and (3) were reported as either 'not work-limited' or 'not DDA disabled' and therefore possibly less likely to be affected by the DDA'2005.

Another useful feature of the LFS data is that it spans several years before and after the DDA'2005 and is therefore useful for two reasons. Firstly, the resulting data contains over one-hundred thousand children aged 16–17. This is particularly important given the proportion of children with disabilities is small but, thanks to the large representative sample, our resulting sub-sample of children with disabilities still counts in the thousands. Secondly, the long time period allows us to use pre-legislation years as a stable benchmark and the post-legislation years allow the DDA'2005 to take effect.

We are interested in the educational and work outcomes for these older children, so we need to combine the LFS variables ILODEFR and CURED to measure this. ILODEFR records the respondent's current labour market status:

"ILODEFR - Basic economic activity (ILO definition) (reported)

(1) In employment
(2) ILO unemployed
(3) Inactive
(4) Under 16″

while CURED is a measure of whether the respondent is currently a student. Using ILODEFR and CURED together we define STATUS, the dependent variable for our analysis:

STATUS

(1) Student
(2) Employed
(3) Unemployed
(4) Inactive (not in the labour market nor student)

In those cases where CURED and ILODEFR identify the child as both active in the labour market and a student, we set those as working more than 20 h per week as (2) Employed and those who work 20 or less per week as a (1) Student.

Finally, it is useful that the LFSs are population-representative surveys and it is possible to cross-link the characteristics of individuals within the same family unit. Given the importance of parental characteristics in children's educational and work choices, we include parents' (or guardians') characteristics within our analysis. We also identify the presence of other children in the family unit.

3.2. Sub-sample of children aged 16 and 17 on August 31st

We are interested in whether older children are in full-time education at a time when education was compulsory up to age 16 (i.e. school-year 11). The LFS does not record which year of study a child is in, so we selected children aged 16 or 17 on August 31st of each survey year, meaning we could determine if they would be in school-year 12 or 13 if still in education. The one caveat is that we only included children from England and Wales because it is only in these countries that only one date, August 31st, was used for school enrolment. We cannot include children from Scotland and Northern Ireland because some discretion was allowed over a child's age of entry into education.

3.3. Summary statistics

Table 1 presents summary statistics for the proportion of children in each disability category. We see that we have tens of thousands of children without any reported disability but we also have several thousand children who report some form of disability.

We are interested in the outcomes for these children, so having defined the variable STATUS from the LFS variables CURED and ILODEFR we have the summary statistics in Table 2. The majority of these children are students. The next largest group is children who are employed and then children who are unemployed. The least frequent

Table 1
Child's disability type.

LFS Variable: DISCURR	Frequency	Percent
(1) Both DDA and work-limiting disabled	6,177	4.27
(2) DDA disabled (current disability) only	2,984	2.06
(3) Work-limiting disabled only	4,060	2.81
(4) Not disabled	131,496	90.86
Total	*144,717*	*100*

Table 2
Child's Status.

Variable: STATUS	Frequency	Percent
(1) Student	102,056	70.52
(2) Employed	27,971	19.33
(3) Unemployed	8,412	5.81
(4) Inactive	6,278	4.34
Total	*144,717*	*100*

Table 3
Explanatory variables.

Variable:	Mean	Min	Max
DDA'2005$_{t \geq Aug2006}$ (legislation dummy)	0.390	0	1
Academic year trend	8.061	1	16
Unemployment rate$_{rt}$ (by region & year)	0.057	.032	.125
Girl	0.494	0	1
Aged 17+	0.490	0	1
Has GCSEs (at grade C or better)	0.795	0	1
# siblings aged 0–4	0.066	0	4
# siblings aged 5–9	0.143	0	4
Employed Mum	0.673	0	1
Employed Dad	0.614	0	1
No Parent (is present in the family unit)	0.038	0	1
Single Mum	0.243	0	1
Employed Single Mum	0.158	0	1
Single Dad	0.040	0	1
Employed Single Dad	0.029	0	1
Mum has A-Levels (or equivalent)	0.356	0	1
Dad has A-Levels (or equivalent)	0.400	0	1
Mum is DDAD & WL	0.118	0	1
Mum is DDAD	0.050	0	1
Mum is WL	0.029	0	1
Dad is DDAD & WL	0.080	0	1
Dad is DDAD	0.038	0	1
Dad is WL	0.023	0	1
Region of usual residence		1	17
(used to generate region dummies)			
Number of observations: 144,717			

Abbreviations: DDAD (Disability Discrimination Act 1995 disabled), WL (work-limited). A-Level examinations are taken at the end of secondary education, usually at age 18.

outcome is inactive children, meaning the child is neither studying nor active in the labour market.

We model the Table 2 outcomes using a rich set of explanatory variables, summarized in Table 3. The main explanatory variable of interest is the binary policy indicator DDA'2005$_{t \geq Aug2006}$, equal to one from August 2006 and zero beforehand. Though the DDA'2005 received Royal Assent in April 2005, it was implemented in stages over the next eighteen months (Department of Work & Pensions 2010, pp.5–6). August 2006 is therefore used as the policy break date in our analysis given it marks the first academic year in which the DDA'2005 legislation was fully enacted. In our sample, 39% of the children are surveyed from August 2006 on, which gives a sufficient sample proportion to evaluate the Act's impact.

We include an 'Academic year trend' to capture the observed secular increase in child education and decline in child employment, beyond the effects of the DDA'2005. Using academic or calendar year for the trend did not noticeably affect the results. We constructed and included an adult unemployment rate variable for each year in each of the 17 regions, using the adult LFS data, to capture general labour market conditions. We did not use a youth unemployment rate as this is endogenously determined with the dependant variable. We found that the results were not robust to models that included different measures of unemployment and different break dates for the DDA'2005 policy variable. It therefore seems important to accurately control for the timing of policy enactments and economic conditions.

We also included the binary variable 'Girl' to allow for gender differences and we interacted this gender variable to allow for differences in various coefficients between boys and girls. The 'Aged 17+' dummy allows for a change in child's age half-way through the final two years of secondary education. 'Has GCSEs' is a variable that identifies if a child achieved GCSEs at grade C or better, and is important in determining who remains in education. '# siblings aged 0–4′and '# siblings aged 5–9′ allows for the presence and number of siblings and, as we will see, there is a notable difference in siblings' influence between boys and girls. A set of parental characteristics are also included such as work status, educational achievement and disability status. As expected, due to age, the proportion of parents with a disability is higher than that of children. For example, the proportion of children who are both with disabilities (DDAD) and work-limited (WL) is 4.27% but is 11.8% for mothers and 8.0% for fathers (including guardians). Region of usual residence identifies Wales and 16 English regions, and is used to model region fixed effects.

3.4. Temporal trends

Before moving on to the multinomial Logit analysis, we illustrate the data we generated to identify temporal trends. Fig. 1 shows, with a split vertical axis, the proportions in each disability group (DISCURR) across time. These proportions seem relatively constant over the period 1997–2012 and there has not been a noticeable drop in the proportion of those without disabilities despite the increased frequency and scope of disability legislation. Importantly, no sudden changes in the disability proportions seem evident at the time of the DDA'2005 legislation and enactment, which might have otherwise suggested a self-reporting bias as documented by Gannon (2009). However, across the whole 1997–2013 time-period, there seems to have been a gradual increase in the proportion of those both work-limited and DDA-disabled at the expense of the proportion of those who are only work-limited.

The graphs in Fig. 2 illustrate the STATUS proportions for each of the four disability groups in Fig. 1. The bottom-right sub-graph in Fig. 2, for children without disabilities and no work limitations, illustrates the benchmark trends: an increasing proportion of students, a decreasing proportion of labour market active children and relatively constant proportions of children who are inactive or unemployed. A similar long-term trend is evident in the other three sub-graphs, but is accompanied with fluctuations that do not coincide with the DDA'2005 legislation and might simply be more evident noise in small samples. The absence of an obvious step-change and the presence of noise is why we need the multivariate analysis in the next section to discern the presence of any policy effects.

4. Methodology

In Section 4.1 we present multinomial Logit estimates for the simultaneous marginal effects on the likelihood of being a student, employed, unemployed or inactive in the labour market. Section 4.2 describes the use of Fairlie-Blinder-Oaxaca decompositions of the binary Logit models to examine differences between children with and without disabilities. It also outlines the DeLeire-Jones method for separating the contributions of disability discrimination and unobserved productivity differences in the Fairlie-Blinder-Oaxaca decompositions.

Throughout we use Logit, rather than Probit, estimation to ensure estimated probabilities add up exactly to sample proportions. In practice, the choice of Logit or Probit makes little difference to the estimated marginal effects. Fairlie-Blinder-Oaxaca decompositions can be carried out in various ways and described using alternative terminologies. To facilitate the interpretation of the results in Section 5, we perform the decompositions by subtracting the outcomes for non-disabled children from outcomes for children with disabilities. Furthermore, we refer to the decompositions as 'coefficient' and 'endowment' effects rather than 'explained' and 'unexplained' effects. We therefore differ slightly from the approach and terminology in Jones (2006) but this does not affect

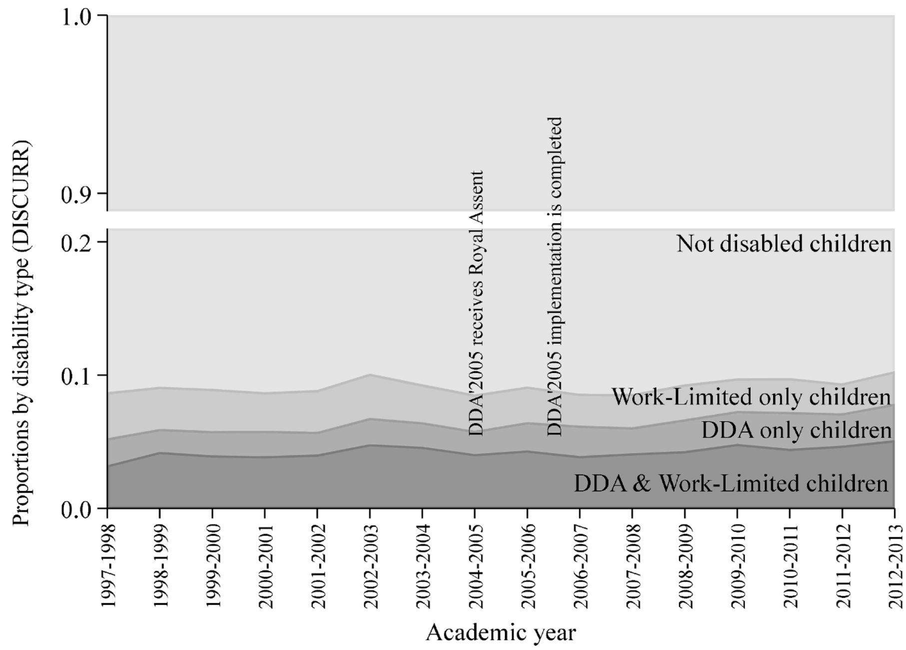

Fig. 1. Proportions with each disability type (DISCURR) across time.

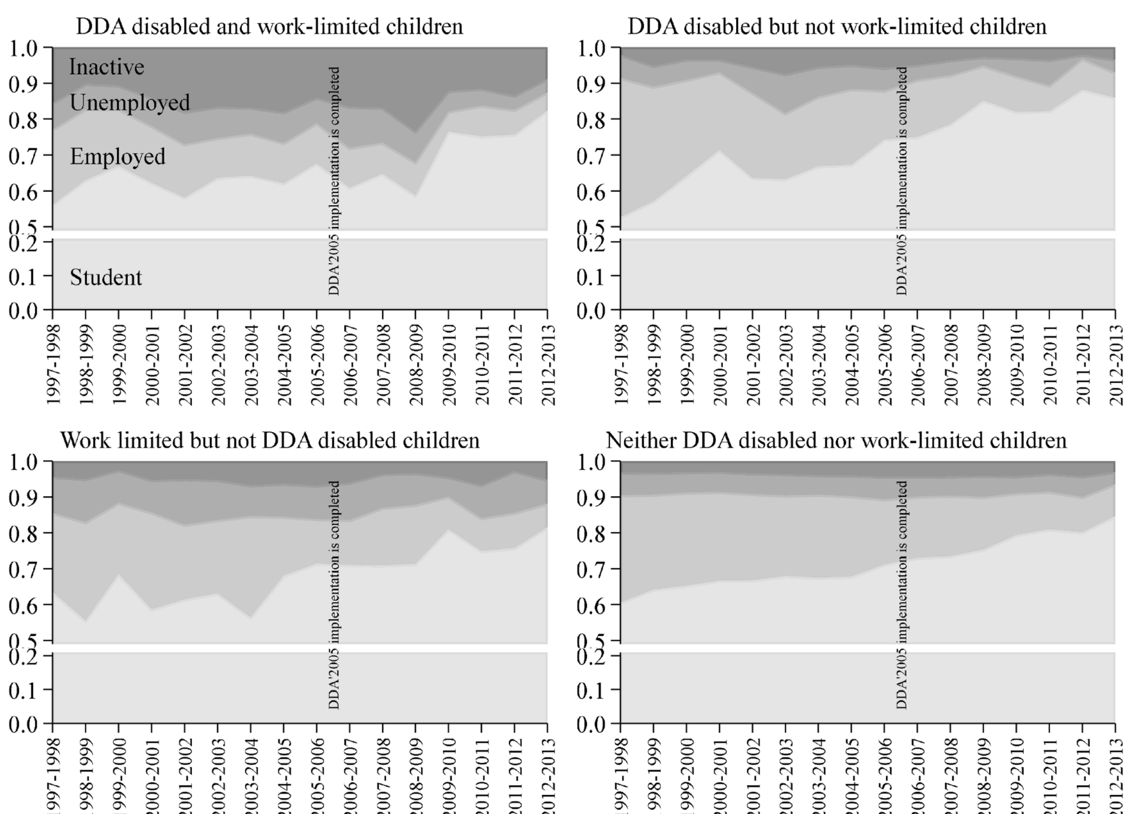

Fig. 2. STATUS for children in four disability states.

the magnitude of the results.

We refrain from performing a difference-in-difference analysis for two reasons. Firstly, because there is some uncertainly and controversy regarding the validity of difference-in-difference analysis in Logit (and Probit) estimates, see Ai and Norton (2003) and Puhani (2008). Secondly, this is not an experiment on an initially homogeneous group of children given, as shown in Fig. 2, the four disability groups clearly start out as very different from one another prior to the DDA’2005.

Throughout, we model boys and girls in the same equations in order to conserve degrees of freedom but we allow for gender interactions with demographic variables to estimate gendered effects. We did attempt to model boys and girls separately but there were insufficient observations for separate estimates on the sub-samples of children with disabilities.

4.1. Multinomial logit marginal effects

In this sub-section, we describe the multivariate estimation method used to analyse these children's responses to the DDA'2005 legislation while controlling for other factors. For each of the four disability groups, we model which one of four potential outcomes (Student, Employed, Unemployed or Inactive) occurred. These four encompass all the possibilities, we therefore model them simultaneously by multinomial Logit regression. Rather than report the resulting parameters or odds ratios (i.e. exponentiated parameters) we take a further statistical step and report the marginal effect for each parameter. Marginal effects are easier to interpret as they indicate the proportionate response in each outcome implied by the estimated parameters.

Marginal effects have additional benefits. One is that, although we have to exclude one outcome as the regression reference category, marginal effects can be calculated for the excluded category. Furthermore, the estimated marginal effects remain unchanged regardless of which reference category is excluded and, by construct, the sum of the marginal effects for any one variable across the four outcomes (horizontally) should add up to zero, which serve as consistency checks.

The multinomial Logit regressions are specified for four outcomes using children who are students as the baseline reference category ($\beta^{(1)}=0$, thus $e^{\beta^{(1)}}=1$):

$$\begin{aligned}
\Pr(STATUS=1)&=\frac{1}{1+e^{X\beta^{(2)}}+e^{X\beta^{(3)}}+e^{X\beta^{(4)}}}\\
\Pr(STATUS=2)&=\frac{e^{X\beta^{(2)}}}{1+e^{X\beta^{(2)}}+e^{X\beta^{(3)}}+e^{X\beta^{(4)}}}\\
\Pr(STATUS=3)&=\frac{e^{X\beta^{(3)}}}{1+e^{X\beta^{(2)}}+e^{X\beta^{(3)}}+e^{X\beta^{(4)}}}\\
\Pr(STATUS=4)&=\frac{e^{X\beta^{(4)}}}{1+e^{X\beta^{(2)}}+e^{X\beta^{(3)}}+e^{X\beta^{(4)}}}
\end{aligned} \tag{1}$$

where $X\beta^{(2)}$ is the equation for children who are employed, $X\beta^{(3)}$ is the equation for unemployed children and $X\beta^{(4)}$ is the equation for inactive children. The marginal effect for each binary explanatory variable is then calculated by the following steps: first simulate each average effect when the binary variable of interest is set to zero and all other variables are set to their means $(\bar{x}_{j,h=0})$, second simulate each average effect when the same binary variable is set to one and the others are set to their mean $(\bar{x}_{j,h=1})$, and finally subtract the first average effect from the second to obtain the marginal effect:

$$ME_h=\left(1-\exp\left(-\sum_{j=1}^{k}\widehat{\beta}_j\bar{x}_{j,h=1}\right)\right)^{-1}-\left(1-\exp\left(-\sum_{j=1}^{k}\widehat{\beta}_j\bar{x}_{j,h=0}\right)\right)^{-1} \tag{2}$$

where $\left(1-\exp\left(-\sum_{j=1}^{k}\widehat{\beta}_j\bar{x}_{j,h=[0,1]}\right)\right)^{-1}$ is the *(cumulative) logistic distribution function* and exp is the natural exponential *e*. Marginal effects on the continuous variables are obtained by calculating the slopes of the cumulative distribution function with respect to the continuous variables, evaluated at the mean values for all the explanatory variables $(\bar{x}_j)$:

$$\begin{aligned}
ME_h&=\frac{\partial\left(1-\exp\left(-\sum_{j=1}^{k}\widehat{\beta}_j\bar{x}_j\right)\right)}{\partial x_h}\\
&=\lim_{\Delta x_h\to 0}\frac{1-\exp\left(-\sum_{j=1}^{k}\left(\widehat{\beta}_j\bar{x}_j+\widehat{\beta}_h\Delta x_h\right)\right)-\left(1-\exp\left(-\sum_{j=1}^{k}\widehat{\beta}_j\bar{x}_j\right)\right)}{\Delta x_h}
\end{aligned} \tag{3}$$

4.2. Fairlie-Blinder-Oaxaca decompositions and Deleire-Jones analysis

In this sub-section, we first outline the Fairlie-Blinder-Oaxaca decompositions (Blinder, 1973; Fairlie, 1999, 2005; Oaxaca, 1973) for differences in outcomes (Student, Employed, Unemployed or Inactive) between children with and without disabilities or work limitations, into components related to differences in average characteristics and differences in responses for the same characteristics. Next, we present the methodology, developed in DeLeire (2001) for continuous outcomes (i.e. wages) and subsequently Jones (2006) for binary outcomes (i.e. employment), to isolate and therefore estimate these discrimination effects. It is worth noting that this interpretation hinges upon the assumptions that any discrimination is orthogonal to the degree of severity of productivity limitations for children with disabilities since we utilise a binary indicator of whether or not a child has work limitations. It also hinges on there being minimal measurement errors on the observable variables and minimal variation in preferences for type of employment or schooling that are correlated with the disability status. If for example, the likelihood of reporting being work-limited varies with disability status, or if children with disabilities have disproportionately higher preferences for jobs for which there are worker-shortages, then these factors can contribute to the explanation for the gap in outcomes.

No decomposition procedure exists for multivariate categorical outcomes, so we carry out four decompositions, one for each outcome (e.g. student) relative to all other combined outcomes. Given the outcomes are binary (e.g. student), rather than linear (e.g. wages), we must use the Fairlie (2005) binary variant of the linear Blinder-Oaxaca decomposition (Blinder, 1973; Oaxaca, 1973) to analyse differences between groups. We use the versatile Stata script 'oaxaca' by Jann (2008) as this can compute the *t*-statistics for the decompositions and allows us to obtain significance levels for the decomposition effects. As suggested by Oaxaca and Ransom (1994), we use pooled parameter estimates to provide 'group-neutral' parameters with which to carry out comparisons between groups. The benefit of the pooled parameter estimates is that they reflect the LFS sample proportions which, in turn, represent the population proportions.

With all this in mind, the Fairlie-Blinder-Oaxaca 'pooled' probability decomposition based on non-linear Logit (or Probit) model estimates is:

$$\begin{aligned}
\underbrace{\frac{\text{Difference in}}{\text{mean outcomes}}}_{\bar{y}^d-\bar{y}^{nd}} &= \overbrace{(\bar{y}^d-\bar{y}^{nd})_{\text{Endowment_effects}}}\\
&= \overline{P}\left(X_j^d\widehat{\beta}^*\right)-\overline{P}\left(X_j^{nd}\widehat{\beta}^*\right)\\
&\quad\underbrace{+\overline{P}\left(X_j^d\widehat{\beta}^d\right)-\overline{P}\left(X_j^d\widehat{\beta}^*\right)+\overline{P}\left(X_j^{nd}\widehat{\beta}^*\right)-\overline{P}\left(X_j^{nd}\widehat{\beta}^{nd}\right)}_{=(\bar{y}^d-\bar{y}^{nd})_{\text{Coefficient_effects}}}
\end{aligned} \tag{4}$$

where $\bar{y}^d$ and $\bar{y}^{nd}$ represent the mean sample averages for the children with disabilities and 'not disabled' respectively. $\widehat{\beta}^d$, $\widehat{\beta}^{nd}$ and $\widehat{\beta}^*$ are Logit (or Probit) estimated parameters in models for the 'with disability', 'not disabled' and 'pooled' samples respectively. X^d, X^{nd} and X^* are the observed data for the same three sub-samples. The first step in deriving the Fairlie (2006) decomposition in Eq. (4) is based on noting that the difference in mean outcomes is the same as the difference in their probabilities: $\bar{y}^d-\bar{y}^{nd}=\overline{P}(X_j^d\widehat{\beta}^d)-\overline{P}(X_j^{nd}\widehat{\beta}^{nd})$. The $\overline{P}(\ldots)$ are the mean probabilities evaluated for the particular combination of X characteristics and β parameters estimated in the two probability models, using the logistic functions if estimated by Logit (or cumulative normal functions if estimated by Probit). The two zero identities $\overline{P}(X_j^d\widehat{\beta}^*)-\overline{P}(X_j^d\widehat{\beta}^*)=0$ and $\overline{P}(X_j^{nd}\widehat{\beta}^*)-\overline{P}(X_j^{nd}\widehat{\beta}^*)=0$ can then be added to the difference in probabilities and after some simple algebraic re-arranging Eq. (4) is obtained. In Eq. (4) the 'endowment effects' are due to differences in characteristics between the two groups and the 'coefficient' effects are due to differences in estimated parameters, which reflect differences in the behaviour of and toward the two groups.

To provide a thorough analysis, two decompositions are carried out for each group (student, employed, unemployed, inactive). This approach accommodates differences in unobserved opportunity costs, which are arguably correlated with health status, for each of the four outcome groups. This is in line with the study on the effect of health status on employment by Brown et al. (2010) who argue that labour market attachment differs amongst adults who are either in training, employed, unemployed, or inactive. This is done by letting d in Eq. (4) represent either the children who are both DDA disabled and work-limited (d=DDAD+WL) or letting d represent children who are DDA disabled but not work limited (d=DDAD).

Next, we use elements of the decompositions in Eq. (4) to focus on the issue of childhood disability discrimination using the approach proposed by Jones (2006, pp.33–34) for the employment outcomes of adults with and without disabilities, which she based on the wage-comparison approach of DeLeire (2001, p.147). Though the signs are reversed compared to the parameterisation in Jones (2006), the magnitudes are unaffected and we can interpret the decompositions using her same approach. Based on the first version (d=DDAD+WL) of our Eq. (4), Jones (2006, eq. (4)) proposes that the coefficient effects represent discrimination plus unobserved productivity differences (UPDs):

$$\left(\bar{y}^{\mathrm{DDAD+WL}} - \bar{y}^{nd}\right)_{\substack{\text{Coefficient}\\ \text{effects}}} = \text{Discrimination} + \text{UPDs} \tag{5}$$

Using Jones (2006, eq.5), we further decompose our Eq. (5) utilising the coefficient effects of the second version (d=DDAD) of our Eq. (4) to isolate the discrimination estimate:

$$\left(\bar{y}^{\mathrm{DDAD}} - \bar{y}^{nd}\right)_{\substack{\text{Coefficient}\\ \text{effects}}} = \text{Discrimination} \tag{6}$$

The differences between the coefficient effects embodied in Eqs. (5) and (6) isolate the unobserved productivity differences (UPDs), see Jones, 2006, eq.6:

$$\left(\bar{y}^{\mathrm{DDAD+WL}} - \bar{y}^{nd}\right)_{\substack{\text{Coefficient}\\ \text{effects}}} - \left(\bar{y}^{\mathrm{DDAD}} - \bar{y}^{nd}\right)_{\substack{\text{Coefficient}\\ \text{effects}}} = \text{UPDs} \tag{7}$$

It is important to note that the ‘coefficient effects’, in Eqs. (5) and (6), are estimates of discrimination and unobserved differences in productivity only to the extent to which the ‘endowment effects’ are accurate estimates of the explainable differences between the two groups. If the ‘endowment effects’ are poorly measured, then ‘coefficient effects’ are better described as ‘unexplained effects’ (e.g. Jones, 1983, but not to be confused with the unexplained-membership effects in Blinder, 1973).

5. Results

In this section we discuss the marginal effects estimates for the multinomial Logits, and the Fairlie-Blinder-Oaxaca and DeLeire-Jones decompositions. We are particularly interested in the DDA’2005 legislation and its impact on boys versus girls. While the other explanatory variables are also relevant, they are primarily included to prevent omitted variable bias.

5.1. Multinomial Logit marginal effects results

Table 4 reports the marginal effects for children who are both DDA disabled and work-limited. This is the group for who we conjectured a

Table 4
Multinomial Logit estimate for DDA’1995 disabled and work-limited children.

	Marginal probabilities† (and standard errors)							
Regressors/Outcomes:	(1) Student		(2) Employed		(3) Unemployed		(4) Inactive	
DDA’2005$_{t\geq Aug2006}$ × Boy	−0.057	(0.027)*	0.007	(0.018)	0.031	(0.014)*	0.018	(0.018)
DDA’2005$_{t\geq Aug2006}$ × Girl	−0.085	(0.030)**	0.049	(0.020)*	0.037	(0.016)*	−0.001	(0.020)
Acad. year trend	0.013	(0.003)**	−0.012	(0.002)**	−0.003	(0.001)*	0.002	(0.002)
Unemployment rate$_{r,t}$	1.993	(0.631)**	−0.114	(0.434)	−0.828	(0.318)**	−1.050	(0.417)*
Girl	−0.031	(0.036)	0.006	(0.026)	−0.030	(0.019)	0.055	(0.022)*
Aged 17	−0.145	(0.012)**	0.059	(0.008)**	0.032	(0.006)**	0.054	(0.008)**
Has GCSEs (grade C+)	0.087	(0.017)**	0.026	(0.011)*	−0.035	(0.009)**	−0.078	(0.012)**
# siblings aged 0–4	−0.039	(0.024)	0.041	(0.015)**	0.007	(0.011)	−0.009	(0.015)
# siblings aged 5–9	−0.032	(0.017)	0.001	(0.012)	0.013	(0.008)	0.018	(0.011)
Employed Mum	−0.089	(0.025)**	0.088	(0.016)**	0.029	(0.013)*	−0.027	(0.018)
Employed Dad	0.044	(0.027)	0.031	(0.018)	−0.017	(0.014)	−0.057	(0.019)**
No Parent	−0.252	(0.053)**	0.068	(0.038)	0.062	(0.022)**	0.122	(0.028)**
Single Mum	−0.094	(0.031)**	0.021	(0.024)	0.027	(0.015)	0.046	(0.019)*
Employed Single Mum	0.073	(0.035)*	0.008	(0.024)	−0.048	(0.018)**	−0.033	(0.024)
Single Dad	−0.043	(0.054)	−0.014	(0.045)	0.015	(0.025)	0.043	(0.030)
Employed Single Dad	0.149	(0.078)	0.054	(0.049)	−0.059	(0.047)	−0.144	(0.061)*
Mum has A-Levels	0.093	(0.015)**	−0.015	(0.009)	−0.035	(0.008)**	−0.043	(0.011)**
Dad has A-Levels	0.111	(0.017)**	−0.050	(0.010)**	−0.028	(0.010)**	−0.032	(0.013)*
Mum is DDAD & WL	−0.062	(0.015)**	0.034	(0.010)**	0.036	(0.008)**	−0.008	(0.010)
Mum is DDAD	−0.005	(0.024)	−0.008	(0.016)	0.031	(0.011)**	−0.017	(0.017)
Mum is WL	−0.032	(0.030)	0.049	(0.017)**	0.001	(0.017)	−0.018	(0.021)
Dad is DDAD & WL	0.019	(0.021)	0.006	(0.014)	−0.009	(0.011)	−0.016	(0.015)
Dad is DDAD	−0.062	(0.032)	0.026	(0.019)	0.012	(0.017)	0.025	(0.024)
Dad is WL	−0.071	(0.040)	0.011	(0.024)	−0.020	(0.025)	0.079	(0.025)**
Girl × Has GCSEs	0.029	(0.025)	0.007	(0.016)	−0.006	(0.014)	−0.031	(0.018)
Girl × # siblings aged 0–4	0.022	(0.039)	−0.094	(0.029)**	−0.009	(0.019)	0.082	(0.022)**
Girl × # siblings aged 5–9	0.051	(0.027)	0.002	(0.018)	−0.006	(0.014)	−0.047	(0.019)*
Girl × Employed Mum	0.121	(0.035)**	−0.072	(0.022)**	−0.034	(0.019)	−0.015	(0.026)
Girl × Employed Dad	−0.047	(0.038)	0.016	(0.025)	0.049	(0.021)*	−0.019	(0.026)
Girl × No Parent	−0.047	(0.068)	0.044	(0.047)	0.016	(0.030)	−0.013	(0.035)
Girl × Single Mum	0.097	(0.045)*	−0.044	(0.034)	−0.010	(0.023)	−0.043	(0.026)
Girl × Single Dad	0.086	(0.080)	0.032	(0.054)	−0.021	(0.049)	−0.097	(0.054)
Girl × Employed Single Mum/Dad	−0.116	(0.051)*	0.069	(0.034)*	0.059	(0.027)*	−0.012	(0.036)
Observations: 6177								
Pseudo R^2: 0.1140								

† These correspond to the marginal effects (Eqs. (2) and (3)) for one Multinominal Logit regression (Eq. (1)).
Abbreviation: DDA’1995 (Disability Discrimination Act 1995).
Notes: * $p < 5\%$, ** $p < 1\%$. Standard errors on marginal effects in (parentheses). Sixteen region dummies included.

significant impact of the DDA'2005 on their education and labour market outcomes. The DDA'2005 legislation significantly reduces the probability of any one such child being a student by 5.7% for boys and 8.5% for girls, and of increases the probability of being employed by 4.9% for girls. While these results support our hypothesis, they also indicate a significant 3.1% and 3.7% increase in the probability of unemployment for boys and girls in this group, and this is perhaps an unintended consequence of the DDA'2005. The results in Table 7 suggest no such unemployment effect for 'not disabled' children, so we do not think we have omitted significant macroeconomic effects.

Other marginal effects in Table 4 also align with expectations. For example, the long-term trend shows an increased probability of being a student instead of being employed or unemployed. Higher regional adult unemployment leads to a higher probability of staying a student and a lower probability of being unemployed or inactive. This makes sense, as unlike adults, most children can continue to be students during unfavourable labour market conditions.

Table 4 also shows that being a Girl is associated with a 5.5% higher probability of being inactive. Being 17 years old, reduces the probability of being a student. Having achieved GCSEs at grades C or more, a proxy for higher aptitude for learning, has a positive effect on the probability of being a student or employed and reduces the probability of unemployment or inactivity. Having siblings increases the likelihood of employment. Parental education and gender-specific factors also play a significant role, with having A-level educated parents leading to a higher chance of being a student. Girls with an employed mother are 12.1% more likely to be a student and 7.2% less likely to be employed. Being a girl with an employed single-parent decreases the probability of being a student by 11.6% and increases the probabilities of being employed or unemployed by 6.9% and 5.9%, respectively.

Tables 5 and 6 report the marginal effects for children who are either DDA disabled or work-limited respectively (but not both). As conjectured in the data section, we found no significant effect of the DDA'2005 legislation on either boys or girls in either of these two sub-samples. Only in Table 6 do we find a slight negative 2.7% effect of the DDA'2005 legislation on the probability that girls will be inactive in the labour market. Though reasonable, this result seems too isolated to attribute it much importance. Significant marginal effects for other variables are in line with expectations, but there are fewer of them, possibly due to the sample sizes of only a few thousand for each sub-sample.

Table 7 reports the marginal effects for children labelled 'not disabled and not work-limited' in the LFS. Though the large sample size of 131,496 is likely to produce significant results, the DDA'2005 has no significant effect on most outcomes. The only significant impact is a 0.7% reduction in the probability of girls being unemployed but this coefficient estimate is small in magnitude and therefore has a small 'size effect'. We are unable to explain this result in the context of the legislation. The result might be spurious insofar as it is unlikely that children without disabilities were indirectly affected by those with disabilities given the majority of the sample (90.86%) consists of the former. The marginal effects for the remaining Table 7 characteristics are well-defined and most achieve higher statistical significance, than in tables 4 to 6, possibly due to the much larger sample size.

Existing research occasionally addresses sampling issues related to adults with disabilities. For instance, Andresen et al. (2008) discuss response rates amongst adults with low-back injuries, and Zambelli-Weiner and Friedman (2012) examine the case of those with visual impairments. However, the research seldom tackles the under- or over-representation of children with disabilities, including those with

Table 5
Multinomial Logit estimate for DDA'1995 disabled, not work-limited children.

Regressors/Outcomes:	Marginal probabilities (and standard errors)							
	(1) Student		(2) Employed		(3) Unemployed		(4) Inactive	
DDA'2005$_{t \geq Aug2006}$ × Boy	0.013	(0.036)	0.021	(0.031)	−0.023	(0.013)	−0.011	(0.010)
DDA'2005$_{t \geq Aug2006}$ × Girl	0.029	(0.036)	0.001	(0.031)	−0.010	(0.014)	−0.019	(0.011)
Acad. year trend	0.015	(0.003)**	−0.017	(0.003)**	0.001	(0.001)	0.001	(0.001)
Unemployment rate$_{r,t}$	0.348	(0.831)	0.003	(0.717)	−0.228	(0.335)	−0.123	(0.244)
Girl	0.161	(0.058)**	−0.108	(0.050)*	−0.037	(0.020)	−0.016	(0.014)
Aged 17	−0.144	(0.015)**	0.117	(0.013)**	0.017	(0.006)**	0.010	(0.005)*
Has GCSEs (grade C+)	0.269	(0.026)**	−0.178	(0.022)**	−0.054	(0.009)**	−0.036	(0.008)**
# siblings aged 0–4	−0.092	(0.033)**	0.080	(0.026)**	0.001	(0.010)	0.012	(0.006)
# siblings aged 5–9	0.013	(0.024)	−0.014	(0.021)	−0.004	(0.009)	0.004	(0.005)
Employed Mum	0.006	(0.034)	−0.020	(0.028)	0.033	(0.016)*	−0.018	(0.010)
Employed Dad	−0.016	(0.044)	0.067	(0.039)	−0.038	(0.016)*	−0.013	(0.011)
No Parent	−0.066	(0.081)	0.034	(0.068)	0.034	(0.023)	−0.003	(0.018)
Single Mum	0.092	(0.052)	−0.090	(0.046)	0.009	(0.016)	−0.011	(0.012)
Employed Single Mum	−0.116	(0.049)*	0.142	(0.043)**	−0.040	(0.019)*	0.014	(0.013)
Single Dad	0.178	(0.104)	−0.145	(0.095)	0.018	(0.026)	−0.051	(0.037)
Employed Single Dad	−0.187	(0.104)	0.135	(0.093)	0.028	(0.031)	0.024	(0.038)
Mum has A-Levels	0.102	(0.018)**	−0.086	(0.016)**	−0.017	(0.008)*	0.001	(0.006)
Dad has A-Levels	0.065	(0.020)**	−0.038	(0.017)*	−0.025	(0.010)*	−0.003	(0.007)
Mum is DDAD & WL	−0.031	(0.022)	0.008	(0.020)	0.025	(0.008)**	−0.002	(0.006)
Mum is DDAD	−0.083	(0.024)**	0.062	(0.020)**	0.018	(0.010)	0.003	(0.008)
Mum is WL	−0.080	(0.046)	0.079	(0.037)*	0.021	(0.017)	−0.020	(0.022)
Dad is DDAD & WL	0.028	(0.030)	−0.027	(0.025)	0.002	(0.012)	−0.002	(0.009)
Dad is DDAD	0.029	(0.031)	−0.022	(0.026)	−0.013	(0.016)	0.006	(0.010)
Dad is WL	0.033	(0.054)	−0.064	(0.048)	0.019	(0.017)	0.012	(0.015)
Girl × Has GCSEs	−0.126	(0.036)**	0.097	(0.031)**	0.017	(0.013)	0.012	(0.010)
Girl × # siblings aged 0–4	0.152	(0.058)**	−0.173	(0.053)**	−0.008	(0.019)	0.030	(0.009)**
Girl × # siblings aged 5–9	0.014	(0.036)	0.025	(0.030)	−0.004	(0.015)	−0.035	(0.013)**
Girl × Employed Mum	−0.045	(0.044)	0.065	(0.037)	−0.025	(0.020)	0.005	(0.014)
Girl × Employed Dad	0.031	(0.054)	−0.041	(0.047)	0.024	(0.021)	−0.013	(0.014)
Girl × No Parent	−0.108	(0.096)	0.046	(0.081)	0.035	(0.027)	0.027	(0.020)
Girl × Single Mum	−0.005	(0.071)	−0.005	(0.065)	−0.013	(0.022)	0.023	(0.015)
Girl × Single Dad	−0.081	(0.112)	0.089	(0.097)	−0.055	(0.045)	0.048	(0.040)
Girl × Employed Single Mum/Dad	0.008	(0.070)	−0.024	(0.062)	0.053	(0.026)*	−0.037	(0.020)
Observations: 2984								
Pseudo R^2: 0.1938								

See Table 4 for notes.

Table 6
Multinomial Logit estimate for work-limited, not DDA'1995 disabled children.

	Marginal probabilities (and standard errors)							
Regressors/Outcomes:	(1) Student		(2) Employed		(3) Unemployed		(4) Inactive	
DDA'2005$_{t\geq Aug2006}$ × Boy	−0.013	(0.036)	−0.010	(0.031)	0.019	(0.019)	0.004	(0.010)
DDA'2005$_{t\geq Aug2006}$ × Girl	−0.034	(0.039)	0.043	(0.033)	0.018	(0.022)	−0.027	(0.012)*
Acad. year trend	0.013	(0.003)**	−0.012	(0.003)**	−0.003	(0.002)	0.001	(0.001)
Unemployment rate$_{r,t}$	1.207	(0.855)	−1.144	(0.736)	0.097	(0.456)	−0.159	(0.244)
Girl	0.033	(0.053)	0.028	(0.045)	−0.042	(0.029)	−0.019	(0.015)
Aged 17	−0.116	(0.015)**	0.092	(0.012)**	0.015	(0.008)	0.009	(0.004)*
Has GCSEs (grade C+)	0.166	(0.021)**	−0.074	(0.017)**	−0.063	(0.011)**	−0.029	(0.007)**
# siblings aged 0–4	−0.033	(0.040)	0.025	(0.033)	0.016	(0.017)	−0.008	(0.011)
# siblings aged 5–9	−0.020	(0.023)	0.010	(0.020)	0.001	(0.012)	0.009	(0.006)
Employed Mum	−0.045	(0.030)	0.092	(0.025)**	−0.028	(0.017)	−0.019	(0.010)
Employed Dad	−0.040	(0.037)	0.056	(0.031)	0.001	(0.020)	−0.017	(0.012)
No Parent	−0.164	(0.065)*	0.104	(0.056)	0.050	(0.029)	0.009	(0.016)
Single Mum	−0.131	(0.045)**	0.047	(0.040)	0.065	(0.021)**	0.019	(0.012)
Employed Single Mum	0.060	(0.045)	−0.008	(0.038)	−0.042	(0.022)	−0.010	(0.013)
Single Dad	−0.032	(0.071)	0.004	(0.065)	0.034	(0.030)	−0.006	(0.017)
Employed Single Dad	0.102	(0.086)	−0.023	(0.075)	−0.072	(0.042)	−0.007	(0.026)
Mum has A-Levels	0.137	(0.018)**	−0.083	(0.015)**	−0.047	(0.011)**	−0.007	(0.006)
Dad has A-Levels	0.075	(0.020)**	−0.041	(0.016)*	−0.036	(0.012)**	0.002	(0.007)
Mum is DDAD & WL	−0.006	(0.021)	0.030	(0.018)	−0.021	(0.012)	−0.004	(0.006)
Mum is DDAD	0.029	(0.034)	−0.046	(0.030)	0.012	(0.018)	0.005	(0.009)
Mum is WL	0.032	(0.032)	−0.003	(0.027)	−0.013	(0.018)	−0.016	(0.011)
Dad is DDAD & WL	−0.042	(0.028)	0.028	(0.023)	0.004	(0.016)	0.009	(0.009)
Dad is DDAD	−0.014	(0.041)	−0.017	(0.034)	0.005	(0.025)	0.025	(0.012)*
Dad is WL	−0.011	(0.035)	0.012	(0.028)	0.012	(0.020)	−0.013	(0.015)
Girl × Has GCSEs	0.019	(0.033)	−0.020	(0.027)	−0.005	(0.017)	0.006	(0.009)
Girl × # siblings aged 0–4	0.078	(0.061)	−0.106	(0.054)*	−0.010	(0.027)	0.038	(0.013)**
Girl × # siblings aged 5–9	−0.020	(0.038)	−0.025	(0.034)	0.034	(0.018)	0.011	(0.009)
Girl × Employed Mum	−0.036	(0.044)	−0.035	(0.037)	0.033	(0.026)	0.039	(0.015)*
Girl × Employed Dad	0.010	(0.051)	−0.014	(0.043)	0.012	(0.029)	−0.007	(0.016)
Girl × No Parent	−0.117	(0.085)	0.058	(0.071)	0.000	(0.041)	0.059	(0.020)**
Girl × Single Mum	0.092	(0.067)	−0.072	(0.060)	−0.023	(0.033)	0.003	(0.016)
Girl × Single Dad	−0.147	(0.104)	0.089	(0.088)	0.025	(0.052)	0.033	(0.029)
Girl × Employed Single Mum/Dad	−0.090	(0.067)	0.061	(0.058)	0.040	(0.034)	−0.012	(0.019)
Observations: 4060								
Pseudo R^2: 0.1322								

See Table 4 for notes.

work-limiting characteristics. The only publication on this issue, of which we are aware, is by Erskine et al. (2017) who highlight the limited data on children with mental health issues in Africa. It seems likely that the presence of children with disabilities in surveys, such as the UK LFS, depends on the sampling of their parents or guardians. Our focus, however, is on the children and we therefore feel justified in applying the available population weights of these children to the analysis. To be more precise, our analysis focuses on the different outcomes for each group of children rather than the proportions of children in each group. Nonetheless, there might still be within-group sampling distortions with respect to the observed outcomes that need to be explored. To this end, in Appendix A, we report population-weighted model estimates as robustness checks for the four models reported in Tables 4 to 7. The results seem largely unaffected by the weighting.

Each UK LFS quarterly dataset includes three weighting variables: PWT (for person analysis), PIWT (for earnings analysis), and PHHWT (for household analysis). These three variables include two-digit number suffixes to indicate the 'vintage' year of the weight. In new editions of existing LFS data, weights of an older vintage might be replaced with newer ones. In Appendix A, we use the PWT weight but are faced with six vintages: PWT03, PWT07, PWT09, PWT11, PWT10, and PWT14 for our data collected in 1997q1 to 2012q4. Appendix A explains how we harmonise these vintages into a single variable PWT and illustrates it.

The resulting harmonized PWT variable is used as a *sampling* weight using the Stata regression syntax option [pweight=PWT] as described in Appendix A. Note that analytic weights are not available in limited-dependant-variable regression models such as logit or multinomial logit. Appendix A Tables A1 to A4 illustrate the four resulting weighted multinomial logit regression results. It is apparent that the population weighting does not noticeably alter the parameter estimates and standard errors of Tables 4 to 7. This suggests that either the unweighted data are already representative of each sub-group of children, or these weights carry no information and therefore do not alter the existing results.

5.2. Fairlie-Blinder-Oaxaca decompositions and deleire-jones results

Here we present results for the Fairlie-Blinder-Oaxaca and DeLeire-Jones decompositions introduced in SubSection 4.2. Fairlie-Blinder-Oaxaca decompositions help us attribute differences between groups to either their characteristics (endowment effects) or to discrimination, behaviour, aptitudes, and health-related productivity (coefficient effects). DeLeire-Jones decompositions use Fairlie-Blinder-Oaxaca 'coefficient effects' to delve deeper into issues of discrimination and productivity.

Table 8 shows clear differences in the prevalence of certain outcomes across the four disability groups. For instance, the proportion 'Employed' is higher amongst 'Not disabled' children than amongst 'DDA disabled and Work-limited' (DDAD+WL) children. Conversely, the proportion of DDAD+WL children who are 'inactive' is higher than amongst the 'Not disabled'. Though we do not report the mean values for the dependant variables across the sub-samples, we observed variations in individual and family characteristics. For instance, DDAD+WL children have a higher prevalence of parents with DDA and/or work-limiting disabilities and a lower proportion of GCSE grades C or better.

Table 9 presents two Fairlie-Blinder-Oaxaca decompositions for each of the four binary outcomes (Student, Employed, Unemployed and Inactive). The first decomposition compares children who are both DDA Disabled and Work-Limited (DDAD+WL) to 'Not disabled' children, while the second compares children who are DDAD but not work-limited

Table 7
Multinomial Logit estimate for neither DDA'1995 disabled nor work-limited children.

	Marginal probabilities (and standard errors)							
Regressors/Outcomes:	(1) Student		(2) Employed		(3) Unemployed		(4) Inactive	
DDA'2005$_{t \geq Aug2006}$ × Boy	0.009	(0.006)	−0.010	(0.005)	−0.002	(0.002)	0.003	(0.002)
DDA'2005$_{t \geq Aug2006}$ × Girl	−0.000	(0.006)	0.009	(0.005)	−0.007	(0.003)**	−0.002	(0.002)
Acad. year trend	0.010	(0.001)**	−0.011	(0.000)**	−0.000	(0.000)	0.001	(0.000)**
Unemployment rate$_{r,t}$	1.306	(0.132)**	−1.263	(0.117)**	0.127	(0.049)*	−0.170	(0.040)**
Girl	0.106	(0.010)**	−0.087	(0.009)**	−0.021	(0.004)**	0.001	(0.003)
Aged 17	−0.139	(0.002)**	0.117	(0.002)**	0.016	(0.001)**	0.006	(0.001)**
Has GCSEs (grade C+)	0.233	(0.004)**	−0.136	(0.004)**	−0.059	(0.001)**	−0.038	(0.001)**
# siblings aged 0–4	−0.013	(0.007)	0.008	(0.006)	−0.000	(0.002)	0.005	(0.002)**
# siblings aged 5–9	0.004	(0.004)	−0.000	(0.004)	−0.003	(0.002)*	−0.001	(0.001)
Employed Mum	−0.052	(0.005)**	0.057	(0.004)**	0.002	(0.002)	−0.007	(0.002)**
Employed Dad	−0.027	(0.006)**	0.049	(0.006)**	−0.013	(0.002)**	−0.009	(0.002)**
No Parent	−0.075	(0.012)**	0.061	(0.010)**	0.014	(0.004)**	−0.001	(0.003)
Single Mum	−0.034	(0.009)**	0.013	(0.008)	0.018	(0.003)**	0.003	(0.002)
Employed Single Mum	0.023	(0.009)**	−0.004	(0.008)	−0.014	(0.003)**	−0.006	(0.003)*
Single Dad	−0.037	(0.015)*	0.009	(0.013)	0.019	(0.004)**	0.009	(0.004)**
Employed Single Dad	0.011	(0.015)	0.004	(0.014)	−0.003	(0.005)	−0.012	(0.004)**
Mum has A-Levels	0.108	(0.003)**	−0.082	(0.003)**	−0.022	(0.001)**	−0.003	(0.001)**
Dad has A-Levels	0.072	(0.003)**	−0.054	(0.003)**	−0.015	(0.001)**	−0.003	(0.001)*
Mum is DDAD & WL	−0.020	(0.004)**	0.010	(0.004)**	0.006	(0.002)**	0.003	(0.001)*
Mum is DDAD	−0.014	(0.006)*	0.013	(0.005)**	0.006	(0.002)*	−0.005	(0.002)*
Mum is WL	0.005	(0.008)	−0.010	(0.007)	0.002	(0.003)	0.003	(0.002)
Dad is DDAD & WL	−0.015	(0.005)**	0.016	(0.005)**	0.003	(0.002)	−0.004	(0.002)*
Dad is DDAD	−0.002	(0.007)	0.010	(0.006)	−0.006	(0.003)	−0.002	(0.003)
Dad is WL	0.001	(0.008)	0.000	(0.007)	0.001	(0.004)	−0.002	(0.003)
Girl × Has GCSEs	−0.034	(0.006)**	0.035	(0.005)**	0.003	(0.002)	−0.005	(0.002)**
Girl × # siblings aged 0–4	−0.014	(0.010)	−0.020	(0.009)*	0.003	(0.003)	0.031	(0.002)**
Girl × # siblings aged 5–9	−0.011	(0.006)	0.013	(0.005)*	0.006	(0.002)*	−0.008	(0.002)**
Girl × Employed Mum	0.022	(0.007)**	−0.016	(0.006)*	−0.007	(0.003)*	0.001	(0.002)
Girl × Employed Dad	−0.006	(0.009)	0.003	(0.008)	0.004	(0.003)	−0.001	(0.003)
Girl × No Parent	−0.138	(0.015)**	0.077	(0.014)**	0.020	(0.005)**	0.041	(0.004)**
Girl × Single Mum	0.006	(0.013)	−0.000	(0.012)	−0.001	(0.004)	−0.005	(0.003)
Girl × Single Dad	0.028	(0.018)	−0.023	(0.017)	−0.008	(0.006)	0.003	(0.005)
Girl × Employed Single Mum/Dad	−0.009	(0.012)	0.006	(0.011)	−0.000	(0.004)	0.003	(0.003)
Observations: 131,496								
Pseudo R^2: 0.1228								

See Table 4 for notes.

Table 8
Mean values in Fairlie-Blinder-Oaxaca decompositions.

	Means for DDAD+WL children	Means for DAD but not WL children	Means for WL but not DDAD children[†]	Means for not DDAD & not WL children
Binary dependent variables:				
Student	0.657	0.728	0.667	0.708
Employed	0.117	0.174	0.184	0.198
Unemployed	0.075	0.055	0.098	0.056
Inactive	0.150	0.043	0.050	0.038

Abbreviations: DDAD (Disability Discrimination Act 1995 disabled), WL (work-limited).

[†] Unused mean values in decompositions.

(DDAD but not WL) to 'Not disabled' children. Following Jones (2006), each pair of decompositions is then used to estimate unobserved productivity differences (Eq. (7)).

All eight 'endowment effects' in Table 9 are statistically significant, indicating the impact of observed characteristics on different outcomes amongst children. The negative overall 'endowment effect' (−0.0975) for the first Table 9 decomposition shows that, based purely on their observed characteristics, DDAD+WL children are less likely to be students than 'Not disabled' children. The remaining 'first decompositions' in Table 9 show these DDAD+WL children are more likely to be employed, unemployed or inactive. The 'second decompositions' in Table 9 yield similar results for children who are DDAD but not work-limited, except that they are less likely to be employed based on their observed characteristics, as indicated by the negative second 'endowment effect' (−0.0060) for children who end up 'employed'.

Table 9 shows statistically significant 'coefficients effects', corresponding to Eqs. (5) and (6), in the first seven of the eight cases. When compared to 'not disabled' children, these indicate a greater propensity for these children to be students and a lower propensity to be employed or unemployed as a consequence of discrimination and unobserved productivity effects. In the bottom row of Table 9, the coefficient effect 0.0860, corresponding to Eq. (5), suggests a higher propensity to be 'inactive' as a consequence of combined discrimination and productivity effects. Only the final coefficient effect −0.0014 is statistically insignificant.

Based on Jones (2006), the final column in Table 9 reports the estimated 'unobserved productivity differences' (Eq. (7)). These are the differences in 'coefficient effects', namely the 'discrimination plus unobserved productivity differences (UPDs)', i.e. Eq. (5) minus 'discrimination' Eq. (6). For instance, the 'Student' coefficient effect for DDAD+WL children (0.0465, Eq. (5)) is greater than for 'DDAD but not WL' children (0.0267, Eq. (6)) by 0.0198 (Eq. (7)). This suggests 57% (=0.0267/0.0465) of the difference is attributable to greater access to education for those with disabilities, and 43%(=0.0198/0.0465) to a relative difference in academic aptitude. For 'Employed' children the 'coefficient effects' are negative and, as expected, the effect is larger for DDAD+WL children (−0.1063) than 'DDAD but not WL' children (−0.0180) as the former includes unobservable health-related productivity differences. The latter coefficient effect captures just disability-related, labour-market discrimination against 'DDA disabled' children to which we can attribute 16.9%(=−0.0180/−0.1063) of the 'coefficient effects' The remainder of this effect, 83.1% (=−0.0883/−0.1063), can be attributed to unobservable health-related

Table 9
Fairlie-Blinder-Oaxaca and DeLeire-Jones decompositions.

	DDAD+WL vs. 'Not disabled'		DDAD but not WL v.s. 'Not disabled'		
	First decompositions:[†]		Second decompositions:[†]		DeLeire-Jones decompostions:[††]
Effects	*Endowment effects:*	*Coefficient effects:*	*Endowment effects:*	*Coefficient effects:*	
Equation:		(5)		(6)	(7)=(5)-(6)
Description:		Discr.+UPDs		Discrimin.	UPDs
Student:					
Raw difference:		−0.054(=0.657–0.708)[†††]		0.020(=0.728–0.708)[†††]	
Decomposition:	−0.0975**	0.0465**	−0.0069*	0.0267**	0.0198
Employed:					
Raw difference:		−0.080(=0.117–0.198)[†††]		−0.024(=0.174–0.198)[†††]	
Decomposition:	0.0261**	−0.1063**	−0.0060**	−0.0180**	−0.0883
Unemployed.					
Raw difference:		0.019=(0.075–0.056)[†††]		−0.001(=0.055–0.056)[†††]	
Decomposition:	0.0429**	−0.0239**	0.0086**	−0.0094*	−0.0145
Inactive:					
Raw difference:		0.112(=0.150–0.038)[†††]		0.005(=0.043–0.038)[†††]	
Decomposition:	0.0263**	0.0860**	0.0065**	−0.0014	0.0874

[*] $p < 5\%$.
[**] $p < 1\%$.
[†] Fairlie decompositions (Eq. (4)).
[††] Difference in coefficient effects.
[†††] Mean values from Table 8.
Abbreviations: DDAD (Disability Discrimination Act 1995 disabled), WL (work-limited), UPDs (Unobserved productivity differences).

productivity differences of children with both DDA disabilities and work limitations. Similarly, negative 'coefficient effects' are shown for the outcome 'Unemployed' (−0.0239, −0.0094), indicating lower unemployment probabilities for children with disabilities versus the other outcomes. The 'coefficient effects' for 'Unemployed' are considerably smaller to those for 'Employed', but are still statistically significant. As for the 'Unemployed' outcome, the 'coefficient effect' for DDAD+WL is larger than that for the 'DDAD but not WL' group, suggesting 61% (=−0.0145/−0.0239) of the effect is attributable to unobservable health-related differences in productivity, while the remainder is attributable to discrimination or differences in access. Finally, Table 9 shows coefficient effects of 0.0860 and −0.0014 for the probability of being 'inactive' (neither in education nor in the labour market). The first effect (0.0860) is large and significant, indicating detrimental 'discrimination plus unobserved productivity differences' effects for DDAD+WL children. The second effect (−0.0014) is small, negative and insignificant, suggesting non-discrimination toward 'DDAD but not WL' children. Thus, differences in inactivity are driven by unobserved differences in productivity (0.0874).

As with the multinomial logit regressions, we conduct robustness checks for the decompositions in Table 9 using population-weighted methods. Regression results for this analysis are presented in Appendix tables A1 to A4. As previously discussed for the multinomial logit regressions, the decomposition analyses compare differences in the outcomes for each group of children rather than the proportions in each group. The population weights therefore correct for any sampling biases within group outcomes rather than biases between group proportions. The findings, detailed in Table B1 of Appendix B, reveal that the weighted results vary minimally from the unweighted ones.

6. Conclusion

Our study offers evidence that the DDA'2005 legislation induced older children with both disabilities and work-limitations to join the labour market (as employed or unemployed), rather than becoming 'inactive' or remaining 'students'. This suggests these children had a higher level of labour market attachment than previously thought and that the legislation was perceived as increasing the returns to early labour market entry by lowering disability-associated barriers. Prior to the DDA'2005 older children with both disabilities and work-limitations may have been over-investing in education or not seeking employment opportunities due to barriers such as labour-market discrimination, limited employment opportunities or limited access to some types of jobs. We are the first to demonstrate this effect empirically, using a large-scale representative survey of children who at the time could choose to end their education when aged 16.

Our multinomial Logit regression analysis, in Section 5.1, shows the DDA'2005 legislation reduced the probability that these children, with both DDA disability and work limitations, remained students and increased the probability they became employed or unemployed (i.e. labour market active). This is our evidence that before the DDA'2005 legislation, these children might have been over-investing in education, as we suggested, to overcome the labour market disability discrimination and health-related productivity gap they might later face. This indicates a significant impact of the DDA'2005 legislation on skill acquisition and labour market participation of older children possessing both DDA-defined disabilities and work limitations. Given the unavailability of these specific children's future earnings and employment histories, it is not possible to gauge the long-term effects of the DDA'2005 legislation. Its impact, however, was most likely superseded by England's 2008 Education and Skills Act, which mandated that all children stay in education or vocational training until the age of 17 starting in 2013. This requirement was extended to the age of 18 in 2015. Nonetheless, the DDA'2005's positive effect of lowering the probability that older children with both disabilities and work limitations become labour market 'inactive' may persist to date. Notably, no statistically robust or economically significant result was detected for any other group of children (DDA disabled only, work-limited only, and 'not disabled) that coincided with the timing of the DDA'2005 implementation.

In Section 5.2, we also looked closely at the issue of discrimination by means of Fairlie-Blinder-Oaxaca and DeLeire-Jones decompositions on outcome prevalence (student, employed, unemployed, inactive) by comparing 'not disabled' children to either children with 'DDA and work-limiting disabilities' or children with just 'DDA disabilities'. The estimated "discrimination effect" explained the largest share of the statistically significant differences between children with disabilities and those without with respect to the education outcome. We found that children with DDA disabilities were more likely to be students due to 'discrimination or access inequality' compared to children without disabilities. This suggests that by design, or regulatory enforcement, schools increase access to children with disabilities compared to those without. There are a variety of channels that could drive this result, such as 'reasonable adjustments' made to teaching or assessment, and increasing access to schooling via improved transportation for children with disabilities. On the other hand, we also show evidence of labour market discrimination given the lower probability of DDA disabled children being employed than children without disabilities, even having controlled for numerous endowment effects and unobserved differences in productivity. Compared to the discrimination effect with respect to being a student, the discrimination effect with respect to being employed explained a much smaller proportion of the differences between children with and without disabilities. Conversely, a large share (83.1%) of the unexplained employment gap between children with and without disabilities is explained by group differences in unobservable work-limiting characteristics. This suggests that future policies and efforts need to be directed towards reducing the health-related productivity gap that currently is not addressed via the 'reasonable adjustments' encoded in the DDA'2005 legislation.

Ethics

Ethics approval was granted by the University of Birmingham under reference number ERNE_0965-Mar2023.

CRediT authorship contribution statement

Marco G. Ercolani: Conceptualization, Methodology, Software, Validation, Formal analysis, Investigation, Resources, Data curation, Writing – review & editing, Visualization, Project administration. **Emiliya Lazarova:** Conceptualization, Methodology, Writing – review & editing.

Data availability

The authors do not have permission to share data.

Appendix A. Population weighted multinomial logit regressions

This appendix presents the implementation and results of population-weighted multinomial logit regressions for childhood outcomes. As described in the main text, we are faced with six non-overlapping 'vintages' of population weights in the sixty quarters of LFS data used in the analysis: PWT03, PWT07, PWT09, PWT11, PWT10, and PWT14. The magnitude of these weights is not relevant, what matters are their relative values to one another. Casual inspection of the weights indicated that they average a mean value of 500 and a standard deviation of 100. To harmonise them, each one of the six weights is normalized to these two characteristics using the formula:

$$\text{PWT}\#\# \ = 500 + \frac{100\ (\text{PWT}\#\# - \ \text{mean}\{\text{PWT}\#\#\})}{\text{s.d.}\{\text{PWT}\#\#\}} \tag{A1}$$

where mean$\{\text{PWT}\#\#\}$ is the mean value and s.d.$\{\text{PWT}\#\#\}$ is the standard deviation of the weight that is being normalised. The six non-overlapping, normalised weights are then combined into the single population-weight variable PWT illustrated in Fig. A1.

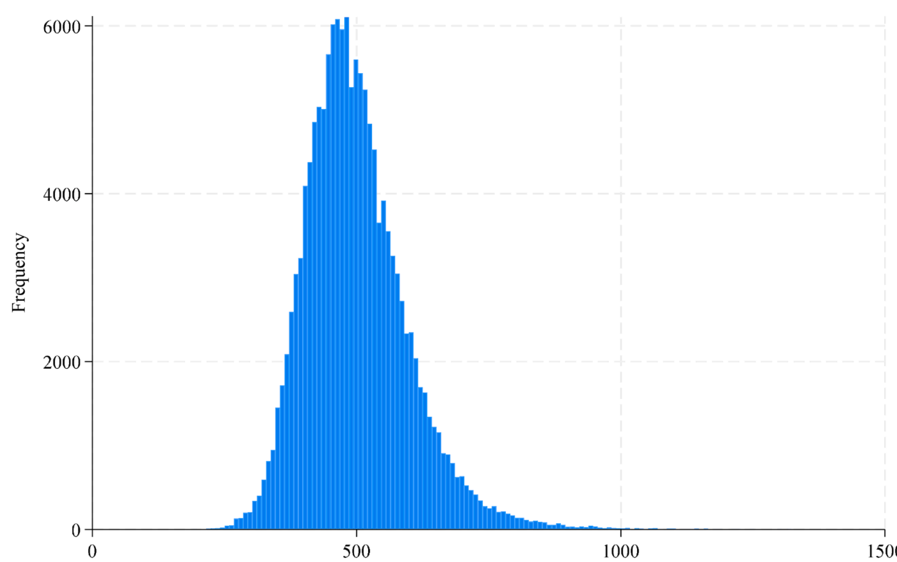

Fig. A1. Histogram for harmonised population weight PWT
Note that the initial weights PWT03 to PWT14 for these children did not include any zeros. This contrasts with the full population datasets, where numerous zeros appear, particularly for older people, to reduce over-representation. This absence of zeros is convenient, ensuring that the sample sizes in Tables A1 to A4 match those in Tables 4 to 7.

Tables A1 to A4 are the weighted regressions corresponding to the unweighted regression in Tables 4 to 7. These are carried out in Stata using the command: mlogit y x1 $\times$ 2 … [pweight=PWT]. The weighting is implemented in the log-likelihood regression by including the individual PWT_i weights after the summation term across all N individuals and before the summation for the $J = 4$ possible outcomes:

$$\ln L = \sum_{i=1}^{N} \mathrm{PWT}_i \sum_{j=1}^{J} (1|Y_i \equiv j) \ln\left(\frac{\exp(\mathbf{x}_i^{'}\boldsymbol{\beta}_j)}{1 + \sum_{k=1}^{J-1}\exp(\mathbf{x}_i^{'}\boldsymbol{\beta}_k)}\right) \tag{A2}$$

where $(1|Y_i \equiv j)$ is an indicator function equal to one if the outcome dependant variable Y_i is in category j and zero otherwise, $\mathbf{x}_i$ is the vector of explanatory variables for individual i, and each $\boldsymbol{\beta}_j$ is a vector of estimated parameters for outcome j. The marginal probabilities are calculated after the regression is estimated. As discussed in the main text, the results are very similar to the unweighted ones in Tables 4 to 7.

Table A1
Weighted Multinomial Logit for DDA'1995 disabled and work-limited children.

	Marginal probabilities† (and standard errors)							
Regressors/Outcomes:	(1) Student		(2) Employed		(3) Unemployed		(4) Inactive	
DDA'2005$_{t\geq Aug2006}$ × Boy	−0.057	(0.027)*	0.007	(0.018)	0.031	(0.014)*	0.018	(0.018)
DDA'2005$_{t\geq Aug2006}$ × Girl	−0.085	(0.030)**	0.049	(0.020)*	0.037	(0.016)*	−0.001	(0.020)
Acad. year trend	0.013	(0.003)**	−0.012	(0.002)**	−0.003	(0.001)*	0.002	(0.002)
Unemployment rate$_{r,t}$	1.993	(0.631)**	−0.114	(0.434)	−0.828	(0.318)**	−1.050	(0.417)*
Girl	−0.031	(0.036)	0.006	(0.026)	−0.030	(0.019)	0.055	(0.022)*
Aged 17	−0.145	(0.012)**	0.059	(0.008)**	0.032	(0.006)**	0.054	(0.008)**
Has GCSEs (grade C+)	0.087	(0.017)**	0.026	(0.011)*	−0.035	(0.009)**	−0.078	(0.012)**
# siblings aged 0–4	−0.039	(0.024)	0.041	(0.015)**	0.007	(0.011)	−0.009	(0.015)
# siblings aged 5–9	−0.032	(0.017)	0.001	(0.012)	0.013	(0.008)	0.018	(0.011)
Employed Mum	−0.089	(0.025)**	0.088	(0.016)**	0.029	(0.013)*	−0.027	(0.018)
Employed Dad	0.044	(0.027)	0.031	(0.018)	−0.017	(0.014)	−0.057	(0.019)**
No Parent	−0.252	(0.053)**	0.068	(0.038)	0.062	(0.022)**	0.122	(0.028)**
Single Mum	−0.094	(0.031)**	0.021	(0.024)	0.027	(0.015)	0.046	(0.019)*
Employed Single Mum	0.073	(0.035)*	0.008	(0.024)	−0.048	(0.018)**	−0.033	(0.024)
Single Dad	−0.043	(0.054)	−0.014	(0.045)	0.015	(0.025)	0.043	(0.030)
Employed Single Dad	0.149	(0.078)	0.054	(0.049)	−0.059	(0.047)	−0.144	(0.061)*
Mum has A-Levels	0.093	(0.015)**	−0.015	(0.009)	−0.035	(0.008)**	−0.043	(0.011)**
Dad has A-Levels	0.111	(0.017)**	−0.050	(0.010)**	−0.028	(0.010)**	−0.032	(0.013)*
Mum is DDAD & WL	−0.062	(0.015)**	0.034	(0.010)**	0.036	(0.008)**	−0.008	(0.010)
Mum is DDAD	−0.005	(0.024)	−0.008	(0.016)	0.031	(0.011)**	−0.017	(0.017)
Mum is WL	−0.032	(0.030)	0.049	(0.017)**	0.001	(0.017)	−0.018	(0.021)
Dad is DDAD & WL	0.019	(0.021)	0.006	(0.014)	−0.009	(0.011)	−0.016	(0.015)
Dad is DDAD	−0.062	(0.032)	0.026	(0.019)	0.012	(0.017)	0.025	(0.024)
Dad is WL	−0.071	(0.040)	0.011	(0.024)	−0.020	(0.025)	0.079	(0.025)**
Girl × Has GCSEs	0.029	(0.025)	0.007	(0.016)	−0.006	(0.014)	−0.031	(0.018)
Girl × # siblings aged 0–4	0.022	(0.039)	−0.094	(0.029)**	−0.009	(0.019)	0.082	(0.022)**
Girl × # siblings aged 5–9	0.051	(0.027)	0.002	(0.018)	−0.006	(0.014)	−0.047	(0.019)*
Girl × Employed Mum	0.121	(0.035)**	−0.072	(0.022)**	−0.034	(0.019)	−0.015	(0.026)
Girl × Employed Dad	−0.047	(0.038)	0.016	(0.025)	0.049	(0.021)*	−0.019	(0.026)
Girl × No Parent	−0.047	(0.068)	0.044	(0.047)	0.016	(0.030)	−0.013	(0.035)
Girl × Single Mum	0.097	(0.045)*	−0.044	(0.034)	−0.010	(0.023)	−0.043	(0.026)
Girl × Single Dad	0.086	(0.080)	0.032	(0.054)	−0.021	(0.049)	−0.097	(0.054)
Girl × Employed Single Mum/Dad	−0.116	(0.051)*	0.069	(0.034)*	0.059	(0.027)*	−0.012	(0.036)
Observations: 6177								
Pseudo R^2: 0.1126								

See Table 4 for notes.

Table A2
Weighed Multinomial Logit for DDA'1995 disabled, not work-limited children.

	Marginal probabilities (and standard errors)							
Regressors/Outcomes:	(1) Student		(2) Employed		(3) Unemployed		(4) Inactive	
DDA'2005$_{t\geq Aug2006}$ × Boy	0.005	(0.038)	0.036	(0.032)	−0.028	(0.014)*	−0.014	(0.012)
DDA'2005$_{t\geq Aug2006}$ × Girl	0.021	(0.036)	0.010	(0.032)	−0.011	(0.014)	−0.020	(0.012)
Acad. year trend	0.015	(0.003)**	−0.017	(0.003)**	0.001	(0.001)	0.001	(0.001)
Unemployment rate$_{r,t}$	0.689	(0.829)	−0.406	(0.711)	−0.166	(0.311)	−0.117	(0.281)
Girl	0.160	(0.057)**	−0.097	(0.050)	−0.042	(0.022)	−0.021	(0.015)
Aged 17	−0.140	(0.016)**	0.114	(0.014)**	0.017	(0.006)**	0.009	(0.005)
Has GCSEs (grade C+)	0.269	(0.027)**	−0.175	(0.023)**	−0.057	(0.009)**	−0.036	(0.008)**
# siblings aged 0–4	−0.083	(0.030)**	0.075	(0.026)**	−0.002	(0.010)	0.010	(0.005)*
# siblings aged 5–9	0.016	(0.026)	−0.017	(0.022)	−0.003	(0.008)	0.003	(0.005)
Employed Mum	0.001	(0.034)	−0.018	(0.027)	0.040	(0.016)*	−0.022	(0.011)*
Employed Dad	−0.011	(0.041)	0.071	(0.036)*	−0.042	(0.014)**	−0.018	(0.011)
No Parent	−0.074	(0.083)	0.043	(0.068)	0.039	(0.024)	−0.008	(0.020)
Single Mum	0.080	(0.050)	−0.077	(0.045)	0.014	(0.016)	−0.016	(0.012)
Employed Single Mum	−0.102	(0.050)*	0.129	(0.043)**	−0.046	(0.018)**	0.019	(0.014)
Single Dad	0.153	(0.118)	−0.110	(0.107)	0.020	(0.030)	−0.063	(0.076)
Employed Single Dad	−0.167	(0.113)	0.103	(0.101)	0.031	(0.031)	0.032	(0.070)
Mum has A-Levels	0.094	(0.019)**	−0.078	(0.016)**	−0.017	(0.008)*	0.000	(0.006)
Dad has A-Levels	0.058	(0.021)**	−0.030	(0.017)	−0.026	(0.011)*	−0.001	(0.007)
Mum is DDAD & WL	−0.026	(0.024)	0.006	(0.021)	0.023	(0.009)**	−0.003	(0.006)
Mum is DDAD	−0.088	(0.024)**	0.064	(0.020)**	0.021	(0.011)	0.004	(0.008)

(continued on next page)

Table A2 (*continued*)

	Marginal probabilities (and standard errors)							
Regressors/Outcomes:	(1) Student		(2) Employed		(3) Unemployed		(4) Inactive	
Mum is WL	−0.065	(0.045)	0.069	(0.036)	0.021	(0.018)	−0.024	(0.024)
Dad is DDAD & WL	0.005	(0.032)	−0.011	(0.027)	0.008	(0.012)	−0.002	(0.011)
Dad is DDAD	0.018	(0.032)	−0.019	(0.026)	−0.007	(0.017)	0.008	(0.010)
Dad is WL	0.018	(0.046)	−0.056	(0.040)	0.027	(0.015)	0.012	(0.016)
Girl × Has GCSEs	−0.126	(0.036)**	0.093	(0.032)**	0.022	(0.012)	0.011	(0.010)
Girl × # siblings aged 0–4	0.132	(0.066)*	−0.162	(0.064)*	−0.002	(0.017)	0.032	(0.009)**
Girl × # siblings aged 5–9	0.010	(0.037)	0.030	(0.031)	−0.007	(0.017)	−0.034	(0.013)*
Girl × Employed Mum	−0.052	(0.044)	0.068	(0.038)	−0.027	(0.018)	0.011	(0.017)
Girl × Employed Dad	0.036	(0.051)	−0.049	(0.046)	0.025	(0.018)	−0.013	(0.016)
Girl × No Parent	−0.111	(0.100)	0.045	(0.084)	0.034	(0.028)	0.032	(0.022)
Girl × Single Mum	0.004	(0.070)	−0.014	(0.066)	−0.018	(0.023)	0.027	(0.015)
Girl × Single Dad	−0.073	(0.120)	0.079	(0.098)	−0.063	(0.040)	0.058	(0.073)
Girl × Employed Single Mum/Dad	−0.004	(0.071)	−0.014	(0.064)	0.063	(0.026)*	−0.044	(0.023)
Observations: 2984								
Pseudo R^2: 0.1882								

See Table 4 for notes.

Table A3
Weighted Multinomial Logit for work-limited, not DDA'1995 disabled children.

	Marginal probabilities (and standard errors)							
Regressors/Outcomes:	(1) Student		(2) Employed		(3) Unemployed		(4) Inactive	
DDA'2005$_{t \geq Aug2006}$ × Boy	−0.018	(0.037)	−0.005	(0.031)	0.021	(0.020)	0.002	(0.011)
DDA'2005$_{t \geq Aug2006}$ × Girl	−0.038	(0.041)	0.049	(0.033)	0.021	(0.023)	−0.032	(0.014)*
Acad. year trend	0.014	(0.003)**	−0.012	(0.003)**	−0.003	(0.002)	0.002	(0.001)
Unemployment rate$_{r,t}$	1.157	(0.883)	−1.018	(0.733)	−0.045	(0.500)	−0.094	(0.274)
Girl	0.039	(0.054)	0.030	(0.046)	−0.048	(0.030)	−0.021	(0.016)
Aged 17	−0.115	(0.015)**	0.092	(0.013)**	0.014	(0.008)	0.009	(0.005)
Has GCSEs (grade C+)	0.164	(0.021)**	−0.070	(0.018)**	−0.066	(0.011)**	−0.029	(0.007)**
# siblings aged 0–4	−0.016	(0.040)	0.010	(0.034)	0.016	(0.018)	−0.010	(0.012)
# siblings aged 5–9	−0.022	(0.023)	0.008	(0.020)	0.002	(0.012)	0.012	(0.006)*
Employed Mum	−0.047	(0.031)	0.090	(0.026)**	−0.024	(0.017)	−0.019	(0.010)
Employed Dad	−0.047	(0.039)	0.063	(0.033)	−0.001	(0.019)	−0.014	(0.012)
No Parent	−0.145	(0.066)*	0.096	(0.055)	0.039	(0.031)	0.010	(0.017)
Single Mum	−0.127	(0.046)**	0.046	(0.040)	0.061	(0.021)**	0.020	(0.012)
Employed Single Mum	0.058	(0.046)	−0.003	(0.040)	−0.044	(0.022)*	−0.011	(0.014)
Single Dad	−0.018	(0.076)	−0.015	(0.068)	0.038	(0.031)	−0.005	(0.017)
Employed Single Dad	0.086	(0.092)	−0.012	(0.079)	−0.081	(0.044)	0.006	(0.029)
Mum has A-Levels	0.135	(0.018)**	−0.082	(0.016)**	−0.047	(0.011)**	−0.006	(0.006)
Dad has A-Levels	0.075	(0.021)**	−0.039	(0.017)*	−0.036	(0.013)**	−0.001	(0.008)
Mum is DDAD & WL	−0.004	(0.021)	0.027	(0.018)	−0.021	(0.012)	−0.001	(0.006)
Mum is DDAD	0.040	(0.035)	−0.055	(0.031)	0.006	(0.018)	0.009	(0.010)
Mum is WL	0.023	(0.032)	0.001	(0.027)	−0.011	(0.018)	−0.013	(0.011)
Dad is DDAD & WL	−0.043	(0.028)	0.033	(0.023)	0.001	(0.015)	0.009	(0.010)
Dad is DDAD	−0.017	(0.041)	−0.011	(0.034)	−0.002	(0.027)	0.031	(0.011)**
Dad is WL	−0.011	(0.035)	0.019	(0.028)	0.002	(0.020)	−0.010	(0.014)
Girl × Has GCSEs	0.018	(0.033)	−0.022	(0.028)	−0.002	(0.018)	0.006	(0.010)
Girl × # siblings aged 0–4	0.055	(0.062)	−0.087	(0.057)	−0.007	(0.027)	0.039	(0.014)**
Girl × # siblings aged 5–9	−0.023	(0.040)	−0.021	(0.034)	0.032	(0.021)	0.012	(0.010)
Girl × Employed Mum	−0.044	(0.047)	−0.035	(0.039)	0.035	(0.027)	0.044	(0.017)**
Girl × Employed Dad	0.009	(0.054)	−0.013	(0.046)	0.014	(0.030)	−0.010	(0.016)
Girl × No Parent	−0.145	(0.085)	0.066	(0.069)	0.009	(0.043)	0.070	(0.021)**
Girl × Single Mum	0.073	(0.067)	−0.065	(0.059)	−0.012	(0.035)	0.004	(0.017)
Girl × Single Dad	−0.145	(0.110)	0.075	(0.094)	0.040	(0.055)	0.029	(0.032)
Girl × Employed Single Mum/Dad	−0.083	(0.069)	0.058	(0.060)	0.039	(0.035)	−0.014	(0.021)
Observations: 4060								
Pseudo R^2: 0.1303								

See Table 4 for notes.

Table A4
Multinomial Logit estimates for neither DDA'1995 disabled nor work-limited children.

	Marginal probabilities (and standard errors)							
Regressors/Outcomes:	(1) Student		(2) Employed		(3) Unemployed		(4) Inactive	
DDA'2005$_{t \geq Aug2006}$ × Boy	0.007	(0.006)	−0.007	(0.005)	−0.003	(0.002)	0.003	(0.002)
DDA'2005$_{t \geq Aug2006}$ × Girl	−0.003	(0.006)	0.012	(0.005)*	−0.007	(0.003)**	−0.001	(0.002)
Acad. year trend	0.010	(0.001)**	−0.011	(0.000)**	0.000	(0.000)	0.001	(0.000)**
Unemployment rate$_{r,t}$	1.379	(0.135)**	−1.337	(0.119)**	0.141	(0.051)**	−0.183	(0.043)**
Girl	0.111	(0.010)**	−0.089	(0.009)**	−0.023	(0.004)**	−0.000	(0.003)

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Table A4 (*continued*)

Regressors/Outcomes:	Marginal probabilities (and standard errors) (1) Student		(2) Employed		(3) Unemployed		(4) Inactive	
Aged 17	−0.139	(0.003)**	0.116	(0.002)**	0.016	(0.001)**	0.006	(0.001)**
Has GCSEs (grade C+)	0.231	(0.004)**	−0.134	(0.004)**	−0.059	(0.002)**	−0.038	(0.001)**
# siblings aged 0–4	−0.014	(0.007)	0.008	(0.006)	−0.000	(0.002)	0.005	(0.002)**
# siblings aged 5–9	0.005	(0.004)	−0.001	(0.004)	−0.003	(0.002)	−0.001	(0.001)
Employed Mum	−0.051	(0.005)**	0.057	(0.005)**	0.002	(0.002)	−0.007	(0.002)**
Employed Dad	−0.029	(0.007)**	0.051	(0.006)**	−0.013	(0.002)**	−0.010	(0.002)**
No Parent	−0.066	(0.012)**	0.056	(0.010)**	0.013	(0.004)**	−0.002	(0.004)
Single Mum	−0.034	(0.009)**	0.013	(0.008)	0.018	(0.003)**	0.003	(0.003)
Employed Single Mum	0.020	(0.009)*	−0.000	(0.008)	−0.014	(0.003)**	−0.006	(0.003)*
Single Dad	−0.035	(0.015)*	0.007	(0.013)	0.018	(0.004)**	0.010	(0.004)**
Employed Single Dad	0.007	(0.016)	0.009	(0.014)	−0.003	(0.005)	−0.013	(0.004)**
Mum has A-Levels	0.105	(0.003)**	−0.079	(0.003)**	−0.023	(0.001)**	−0.003	(0.001)**
Dad has A-Levels	0.071	(0.003)**	−0.053	(0.003)**	−0.015	(0.001)**	−0.003	(0.001)*
Mum is DDAD & WL	−0.019	(0.004)**	0.010	(0.004)*	0.006	(0.002)**	0.003	(0.001)
Mum is DDAD	−0.013	(0.006)*	0.012	(0.005)*	0.006	(0.002)*	−0.005	(0.002)*
Mum is WL	0.009	(0.008)	−0.012	(0.007)	0.001	(0.003)	0.002	(0.003)
Dad is DDAD & WL	−0.016	(0.005)**	0.016	(0.005)**	0.004	(0.002)	−0.004	(0.002)*
Dad is DDAD	−0.004	(0.007)	0.011	(0.006)*	−0.006	(0.003)	−0.001	(0.003)
Dad is WL	0.003	(0.008)	−0.000	(0.007)	0.001	(0.004)	−0.004	(0.003)
Girl × Has GCSEs	−0.034	(0.006)**	0.036	(0.005)**	0.003	(0.002)	−0.005	(0.002)*
Girl × # siblings aged 0–4	−0.010	(0.010)	−0.024	(0.009)**	0.002	(0.004)	0.031	(0.002)**
Girl × # siblings aged 5–9	−0.011	(0.006)	0.014	(0.006)*	0.006	(0.003)*	−0.008	(0.002)**
Girl × Employed Mum	0.018	(0.008)*	−0.014	(0.007)*	−0.006	(0.003)	0.001	(0.003)
Girl × Employed Dad	−0.008	(0.009)	0.003	(0.008)	0.005	(0.004)	−0.001	(0.003)
Girl × No Parent	−0.150	(0.016)**	0.084	(0.014)**	0.022	(0.005)**	0.043	(0.004)**
Girl × Single Mum	0.002	(0.013)	0.001	(0.012)	0.001	(0.004)	−0.005	(0.004)
Girl × Single Dad	0.024	(0.019)	−0.020	(0.017)	−0.007	(0.007)	0.004	(0.005)
Girl × Employed Single Mum/Dad	−0.006	(0.012)	0.003	(0.011)	−0.000	(0.004)	0.003	(0.004)
Observations: 131,496								
Pseudo R^2: 0.1216								

See Table 4 for notes.

Appendix B. Population weighted decompositions

In this appendix the implementation and results of population-weighted Fairlie-Blinder-Oaxaca decompositions are reported. The harmonised individual weight PWT is the one presented in Appendix A. Implementation of the weighted analysis simply involves using the Stata regression syntax option [pweight=PWT] with the latest 2023 release of the 'oaxaca' command by Jann (2008) as this option is not available in some earlier releases.

The weighting is implemented on the (binary) logit regression used to carry out the decompositions. This is a simple implementation of the regression Eq. (A2) where there are just $J = 2$ outcomes. The results of the decompositions are reported in Table B1 and they are little changed from those in the unweighted decompositions reported in Table 9.

Table B1
Fairlie-Blinder-Oaxaca and DeLeire-Jones weighted decompositions.

	DDAD+WL v.s. 'Not disabled' First decompositions:[†]		DDAD but not WL v.s. 'Not disabled' Second decompositions:[†]		DeLeire-Jones decompositions:[††]
Effects	*Endowment effects:*	*Coefficient effects:*	*Endowment effects:*	*Coefficient effects:*	
Equation:		(5)		(6)	(7)=(5)-(6)
Description:		Discr.+UPDs		Discrimin.	UPDs
Student:					
Raw difference:	−0.054(=0.657–0.708)[†††]		0.020(=0.728–0.708)[†††]		
Decomposition:	−0.0971**	0.0443**	−0.0068*	0.0250**	0.0193
Employed:					
Raw difference:	−0.080(=0.117–0.198)[†††]		−0.024(=0.174–0.198)[†††]		
Decomposition:	0.0260**	−0.1072**	−0.0062**	−0.0184**	−0.0888
Unemployed.					
Raw difference:	0.019=(0.075–0.056)[†††]		−0.001(=0.055–0.056)[†††]		
Decomposition:	0.0430**	−0.0231**	0.0087**	−0.0079	−0.0152
Inactive:					
Raw difference:	0.112(=0.150–0.038)[†††]		0.005(=0.043–0.038)[†††]		
Decomposition:	0.0255**	0.0886**	0.0065**	−0.0009	0.0895

* $p < 5\%$,.
** $p < 1\%$.
† Fairlie decompositions (eq. (4)).
†† Difference in coefficient effects.

††† Mean values from Table 8.
Abbreviations: DDAD (Disability Discrimination Act 1995 disabled), WL (work-limited), UPDs (Unobserved productivity differences).

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