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How do childhood ADHD symptoms affect labour market outcomes?

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ABSTRACT

Inattention, hyperactivity and impulsivity are the main symptoms of ADHD, which affects up to one in ten European and North American children. Existing research shows these symptoms are associated with school exclusion and poor academic performance during childhood and adolescence. Using the British Cohort Study (n = 17,196 people born in April 1970), this is the first study of relationships between ADHD symptoms measured during childhood (age 10) and labour market outcomes measured beyond early adulthood (ages 26–46); and the first to explore the role of childhood circumstances (at birth) and academic performance (ages 10 and 26) in explaining those relationships. A one standard deviation increase in childhood symptoms reduced employment by up to two percentage points and pay by up to four percentage points. Differences in academic performance at age 10 accounted for almost half the observed variation in employment outcomes, indicating a possible role for educational interventions in schools.

1. Introduction

Economic growth and performance are determined by human capital. Human capital is a multidimensional construct encompassing different domains, including cognitive abilities and non-cognitive behavioural traits (Heckman and Rubenstein, 2001), many of which are evident and develop first during childhood. Each dimension plays a different role in the process of human development and the determination of key outcomes related to health and wellbeing, including labour market performance (Atkins et al., 2020).

Strong evidence links a wide range of non-cognitive behavioural traits during childhood to labour market outcomes in adulthood (Attanasio et al., 2020). For example, a literature review by Goodman et al. (2015) found associations between childhood self-perception, motivation, self-control, social skills, resilience, and emotional health and adulthood labour market outcomes including income, employment, earnings, and job satisfaction. Early interventions to support the development of such non-cognitive behavioural traits are shown to be highly (cost-) effective in terms of advancing human capital across the lifespan, particularly among children from the most disadvantaged backgrounds (Cunha et al., 2010; Currie, 2020).

This paper focuses on the labour market impacts of three specific non-cognitive traits: inattention, hyperactivity and impulsivity.[1] These are of particular interest because they are the primary symptoms of attention deficit hyperactivity disorder (ADHD) (Currie and Stabile, 2006; Faraone et al., 2003) (APA, 2017), one of the most common mental health disorders affecting school-aged children (Chorniy et al., 2018). Prevalence rates for childhood ADHD are 3–5% in Europe (Kooij et al., 2019) and 2–10% in the USA (Fletcher, 2014). Diagnosis during childhood varies by socio-economic characteristics (Russell et al., 2014), cognitive ability (Milioni et al., 2017), and gender (NICE, 2018). Roughly 80% of children with ADHD continue to exhibit symptoms into adolescence which often persist into adulthood (Faraone et al., 2003; Kooij et al., 2019). Once diagnosed, treatment for ADHD encompasses both medication and behavioural interventions (NICE, 2018) and represents a sizable demand on healthcare resources (Chorniy et al., 2018).

By focusing on diagnosis, the current evidence inevitably excludes people with ADHD who are undiagnosed and those with sub-threshold symptoms, and therefore may not accurately capture the full impact on labour market outcomes. This is particularly relevant for females and people in low socioeconomic subgroups, who are disproportionately less likely to receive an appropriate ADHD diagnosis (NICE, 2018).

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[1] The US National Institute of Mental Health defines these symptoms as follows. Inattention: having difficulty staying on task, sustaining focus and staying organised. Hyperactivity: when a person may seem to move about constantly including in situations when it is not appropriate, or excessively fidgets, taps, or talks. Impulsivity: when a person may act without thinking or have difficulty with self-control.

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Additionally, the focus of existing studies on an ADHD diagnosis means that little is known about how the three non-cognitive traits (inattention, hyperactivity and impulsivity) may have differential effects on labour market outcomes. Inattention, for example, is known to affect educational performance more strongly during adolescence and early adulthood than symptoms of hyperactivity (Salla et al., 2016) but Gordon et al. (2019) and Christiansen et al. (2021) found no studies that examined whether similar differences persist in terms of labour market outcomes during adulthood. Thus existing evidence cannot provide a reliable guide as to which children are at highest risk of poor outcomes and therefore have the most to gain from early interventions to support their development.

The aim of this study is to explore the impacts of different ADHD-related symptoms on labour market outcomes in the UK. Almost all existing evidence is based in the USA, where health, education and labour markets function differently to the UK and other European countries. Our study exploits panel data from the British Cohort Study (BCS), a nationally representative birth cohort study which begins in April 1970 and follows people up to the present day. The dataset is exceptional because, to our knowledge, no other European cohort study collects person-level data on non-cognitive behavioural traits during childhood as well as labour market outcomes during adulthood.

Our first research question explores the impact of different ADHD-related symptoms on labour market outcomes in the UK:

RQ1. What is the relationship between (i) inattention and (ii) hyperactivity/impulsivity symptoms measured during childhood on people's employment and pay during adulthood (ages 26–46); and do these relationships vary by gender, age and degree status?

If ADHD does affect labour market outcomes during adulthood, then an important question is the extent to which this may be due to (can be explained by) differences in socioeconomic circumstances at birth and educational attainment observed during childhood and young adulthood. This would have implications for the timing and nature of interventions to support people with ADHD symptoms to lead more fulfilling working lives. Thus our second research question is:

RQ2. To what extent can any observed relationships between ADHD symptoms during childhood and employment and pay during adulthood be explained by differences in socioeconomic status at birth and educational attainment at ages 10 and 26?

2. Methods

2.1. The British Cohort Study (BCS)

The BCS collected individual-level data approximately every four years on a representative sample of 17,196 people born in the United Kingdom between 5 April and 11 April 1970. Data was collected using questionnaires which are proxy-completed by the participant's mother or main guardian during childhood and self-completed during adulthood. Separate tasks were completed in school by participants (e.g. maths tests) and the participant's schoolteacher (e.g. to identify behavioural issues) when participants were aged 10. The majority of data was returned by post and, more recently, online.

As with other longitudinal cohort studies, the BCS exhibits non-random sample attrition (Mostafa and Wiggins, 2015), meaning that over time the people who continue to respond become less representative of the original sample. In the BCS, non-response has been shown to be associated with gender and the socioeconomic status of parents at birth (Mostafa and Wiggins, 2015).

2.2. Variables

2.2.1. Employment and pay (outcome variables)

Two outcome variables (used in separate regression models) are derived from data collected at six time points (ages 26, 29, 34, 38, 42 and 46): employment (1 = employed; 0 = not employed) and, for people employed, the natural log of inflation-adjusted weekly pay (2019 British Pounds).

We derive employment from a single question about current labour market status which has six possible responses (employed: full time, part-time, self-employed; not employed: unemployed, long-term sickness, full-time education).

Inflation-adjusted weekly pay is calculated using a BCS-derived measure of net pay which captures pay from all employment categories (i.e., full-time; part-time; self-employed). We adjust this measure to reflect differences in the net pay period (which varies in BCS between individuals and time points) and inflation using HM Treasury's GDP deflator (GOV.UK, 2022). Where weekly net pay is lower than £ 2.72 (exponential of 1 natural log unit), we code this information as missing (37 observations), as this could represent a coding error and we cannot be sure of the intended value.

2.2.2. ADHD-related symptoms (independent variables of interest)

Two independent variables of interest (used in separate regression models) are derived from data collected from the participants' schoolteacher at age 10: an inattention scale, which ranges from 0 (no symptoms) to 230 (extreme symptoms), and a hyperactivity and impulsivity scale (hereafter 'hyperactivity scale'), which ranges from 0 (no symptoms) to 184 (extreme symptoms).

These two scales are calculated using responses to selected items from the Conners' Hyperactivity Scale and the Rutter Child Behavior questionnaires, which were prominent measures of behavioural, social and academic issues among children during the 1980s (Table A1 lists these items). These items were selected on the basis of previous literature (Galéra et al., 2011; Salla et al., 2016) and a confirmatory factor analysis (full details are reported separately in Rajah et al., 2021) and are aligned with the American Psychological Association's current definition of ADHD.

In all our analyses and descriptive statistics, a higher score indicates more severe ADHD symptoms. However, as explained below, we reverse the ADHD symptoms scale when calculating the concentration index and concentration curves. In the regression models, we also adjust the two scales to a common scale where the mean value is 0 and the standard deviation is 1. This enables us to interpret our regression results in terms of the labour market response to a one standard deviation change in each scale.

2.2.3. Socioeconomic circumstances at birth and educational attainment during childhood and young adulthood (independent variables used in RQ2)

As a measure of socioeconomic circumstances at birth (age 0), we use the participant's father's age of leaving education (years), which is measured in the proxy-completed questionnaire at birth in 1970. As a measure of educational attainment at age 10, and indicator of cognitive skills, we use a summary measure of mathematical ability which is derived from 73 items in the 'Friendly Maths Test' that was administered to 11,685 participants (61%) at school in 1980 and involves answering questions about algebra and statistics. As a measure of educational attainment at age 26, we use the participants' degree status (1 = bachelor's degree or higher; 0 = no degree) which is derived from a question at age 26 about the participants' highest educational qualification. Where there were missing values at age 26, we used values reported at the next time point that the relevant question was answered, under the assumption that this would most likely have been their education status at age 26.

2.2.4. Other independent variables

Other variables used in the regression analyses and/or to define subgroup analyses were: gender (0 = Male; 1 = Female); age (ordinal variable); marital status (recorded at all time points with six categories and used to derive a binary variable: 0 = not currently married or in a civil partnership; 1 = currently married or in a civil partnership); London resident (recorded at all time points and used to generate a binary variable derived from responses to questions about the participants' geographic region: 0 = living outside of London; 1 = living in London).

2.3. Descriptive statistics and bivariate analyses

Descriptive statistics are presented for all variables listed above, split by gender (Table 1). Inequalities in the distribution of socioeconomic circumstances (age 0), educational attainment (ages 10 and 26) and weekly pay (age 26–46 combined) across the two ADHD symptom scales is assessed using Spearman's rank order correlation. The mean values of each of these variables were also plotted against ADHD symptom quintile (Fig. 2).

The concentration index (CI) (Clarke and Van Ourti, 2010; O'Donnell et al., 2016; Wagstaff, 2005) was additionally used (Fig. 3) to measure inequality in the distribution of pay against rank of ADHD symptoms as follows:

$$CI_{mtg} = \frac{2}{N\mu}\sum_{i=1}^{n} y_i r_i - 1 - \frac{1}{N} \tag{1}$$

where m is one of either inattention or hyperactivity; g is gender; y_i is the value of inflation-adjusted weekly pay at time point t (i.e. ages 26, 29, 34, 38, 42, 46) for each individual (i = i….n) for n individuals in the dataset; μ is the mean value of y_i for all individuals; $r_i = i/N$ is the fractional rank of individual i in the distribution of m scale where $i = 1$ is the individual with the most severe ADHD-related symptom on that scale and $i = N$ is the individual with the least severe symptoms. ADHD symptoms are ordered this way (in reverse) for consistency with other more conventional uses of the concentration index, where i = 1 would be the individual who is "least well off" (conventionally in terms of their income). Thus, in our setting, a negative value of CI indicates a disproportionate concentration of y in people with more severe ADHD symptoms, and a positive value indicates a disproportionate concentration of y in people with less severe ADHD symptoms. Bounded between − 1 and 1, a value of zero would indicate perfect equality in the distribution of y across the selected ADHD symptom scale. Tests of the null hypotheses that the index value equals 0 and that there is equality in the concentration index values between each time point were conducted. The distribution of weekly pay by ADHD symptom scale (m), age (t) and gender (g) is also presented using concentration curves, which show the cumulative share of weekly pay against the rank of ADHD symptoms (increasing in severity) (Fig. A1), and using plots of the mean values of weekly pay (y) against ADHD symptom quintiles (Fig. 3).

2.4. Regression analysis

First, we assess the relationship between ADHD symptoms and employment using a multilevel logistic regression model. Two separate models are used with two different independent variables of interest, which are the inattention and hyperactivity scales. The model accounts for the clustering of multiple employment observations within individuals collected at six different ages by allowing the individual level variance to be partitioned into e_i and u_{it}, as described below:

$$Y_{it} = log\frac{p}{1-p} = \beta_0 + \beta_1 X_{it} + \beta_2 Z_i + \beta_3 M_i + e_i + u_{it} \tag{2}$$

wherein $Y_{i,t}$ is the log odds of employment and p is the probability of employment for each individual i (i = i…n) for n individuals at time point t. In this model, M_i is the independent variable of interest (i.e., the inattention or hyperactivity scale), X_{it} is a vector of independent time varying variables, Z_i is a vector of time-invariant variables, e_i reflects the residuals for individual i, and u_{it} reflects the residuals for individual i at time t. Error terms are assumed to be identical and independently distributed.

Second, we estimate a multilevel linear model to assess the relationship between ADHD symptoms and pay. The model is conditional on people being employed (i.e. only those that are employed are included in the model). As previously, the model is run twice, separately for the inattention and hyperactivity scales and accounts for clustering of pay observations within individuals across six different ages:

$$Y_{it} = \beta_0 + \beta_1 X_{it} + \beta_2 Z_i + \beta_3 M_i + e_i + u_{it} \tag{3}$$

wherein $Y_{i,t}$ is the natural log of the net weekly inflation-adjusted pay.

For each ADHD symptom scale, the results of both models are presented in five stages (i. to v.) in which additional covariates are added to the model sequentially (Table 2 and Table 3). The first two stages (i. to ii.) address RQ1 and include factors that could be associated with labour market outcomes and/or ADHD symptoms (these are gender, region and marital status). The remaining three stages (iii. to v.) address RQ2 by adding (in chronological order) socioeconomic circumstances at birth (age 0) and educational attainment at ages 10 and 26. Following Cutler and Lleras-Muney (2010), we assess the change in β_3 (coefficient of interest) that occurs after the addition of each variable (when compared to model ii.) to determine the extent to which that variable can explain the relationship between ADHD symptoms and labour market outcomes.

To assess variation in the relationship between ADHD symptoms and labour market outcomes, the fully adjusted model (v.) is run separately multiple times by gender, age group and degree status. These three demographic characteristics are determined for each individual prior to the labour market outcome measures. The resulting model coefficients are used to predict labour market outcomes (dependent variable), based on the observed values for each individual, and these predictions are presented graphically in smoothed plots using the generalised additive model (GAM; Yee, 2016) (Fig. 4 and Fig. 5).

2.4.1. Inverse probability weighting (sensitivity analysis)

To address the possibility that sample attrition may bias our results we conducted sensitivity analyses using data collected at two time points (t = age 26 and 46). This involved generating survey weights using inverse probability weighting models, separately for each time point, and then comparing the results of cross-sectional regression analyses of employment (similar to Eq. 2 above, although using a linear probability model to aid the interpretation of coefficients without use of marginal effects) and pay (Eq. 3 above) at each time point with and without the survey weights attached to each individual. The survey weights are designed to re-balance the distributions of the participants in the regression analyses so that the relative importance of each participant's characteristic is weighted according to the importance of the characteristics of those who dropped out (Mostafa and Wiggins, 2015).

The inverse probability weighting model predicts non-response at a particular time point using variables that were used by Mostafa and Wiggins (2015) in a previous examination of attrition in the BCS. These are: gender, mother or main guardian's marital status (binary variable defined above), father's work classification (five categories: professional, clerical/non-manual, unskilled manual, lowest grade workers, other), mother's region of birth (binary variable: born in England or Ireland; not in England or Ireland), mother's age at delivery of participant (five categories: <20, 20–24, 25–29, 30–34, >=35) and father's age of leaving education (five categories: <=14, 15, 16, 17, >=18). These are proxy-reported by the participant's mother or main guardian at birth in 1970. Ages 26 and 46 were chosen as the appropriate time points to investigate because they represent the first and last labour market outcomes in our analyses. Since we anticipate that attrition would be less pronounced at age 26 and more pronounced at age 46, we are confident that this adequately captures the effects of attrition over time within our dataset.

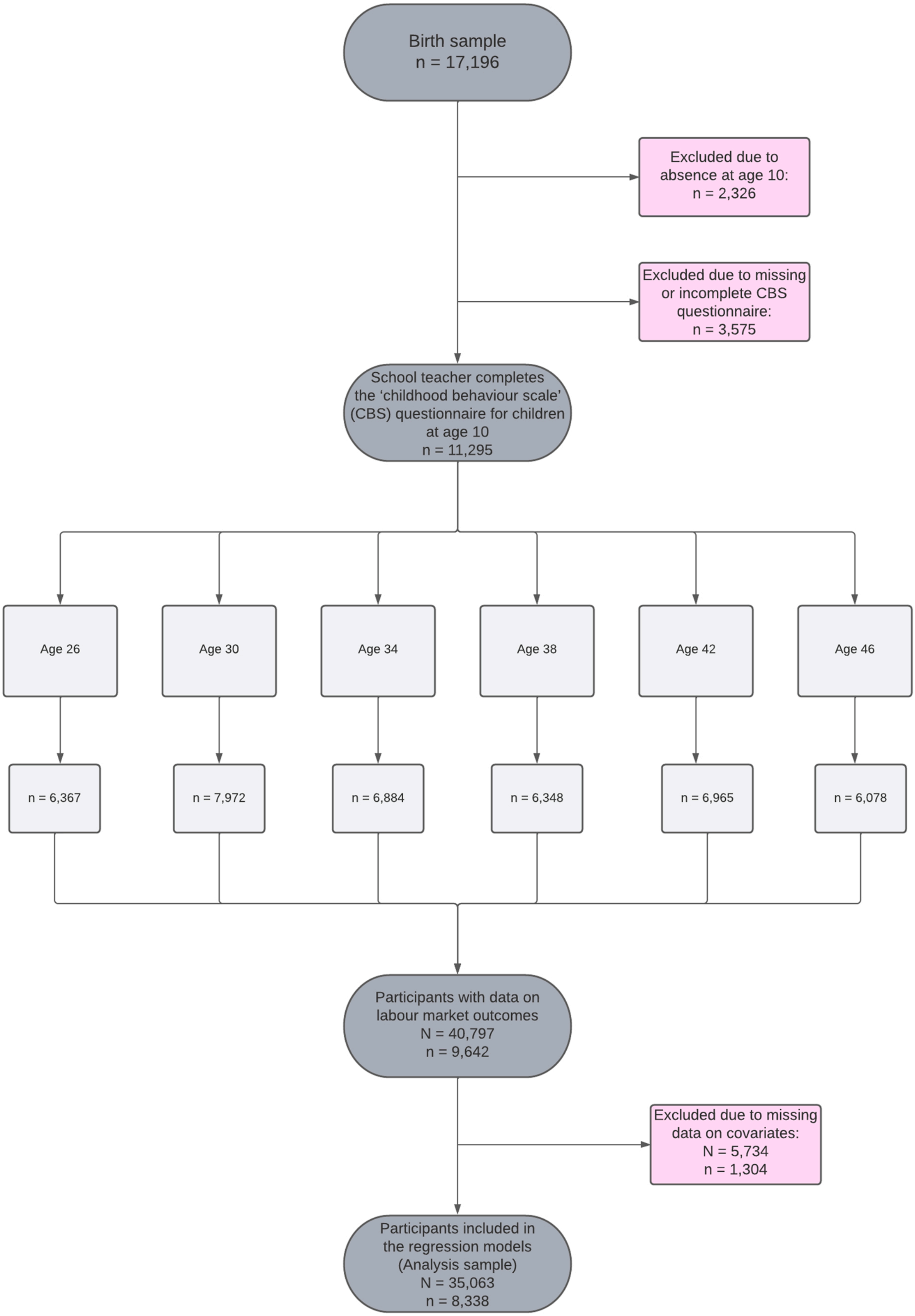

Fig. 1. Data Flow Diagram

Table 1
Descriptive Statistics

	Male (N = 4151)	Female (N = 4187)	Overall (time invariant) (N = 8338)	26 (N = 5243)	29 (N = 6940)	34 (N = 6029)	38 (N = 5548)	42 (N = 6062)	46 (N = 5241)	Overall (time varying) (N = 35063)
Gender										
Male	n/a	n/a	4151 (49.8%)	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Female	n/a	n/a	4187 (50.2%)	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Location										
Living outside	3757 (89.7%)	3757 (89.7%)	7539 (90.4%)	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Living in London	430 (10.3%)	430 (10.3%)	799 (9.6%)	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Degree Status (Age 26)										
No Degree	3513 (83.9%)	3513 (83.9%)	6926 (83.1%)	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Degree	674 (16.1%)	674 (16.1%)	1412 (16.9%)	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Age Of Leaving Full Time Education										
Mean (SD)	18.4 (3.58)	18.4 (3.58)	18.3 (3.52)	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Median [Min, Max]	17.0 [14.0, 34.0]	17.0 [14.0, 34.0]	17.0 [14.0, 38.0]	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Missing	39 (0.9%)	39 (0.9%)	109 (1.3%)	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Father’s Age of Leaving Full Time Education										
Mean (SD)	15.9 (2.34)	15.9 (2.34)	15.9 (2.36)	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Median [Min, Max]	15.0 [0, 30.0]	15.0 [0, 30.0]	15.0 [0, 38.0]	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Marital Status										
Not married	2587 (61.8%)	2587 (61.8%)	5492 (65.9%)	3692 (70.4%)	3849 (55.5%)	2728 (45.2%)	2127 (38.3%)	2218 (36.6%)	1937 (37.0%)	16551 (47.2%)
Married or in a civil partnership	1600 (38.2%)	1600 (38.2%)	2846 (34.1%)	1551 (29.6%)	3091 (44.5%)	3301 (54.8%)	3421 (61.7%)	3844 (63.4%)	3304 (63.0%)	18512 (52.8%)
Hyperactivity Rating										
Mean (SD)	39.8 (36.6)	39.8 (36.6)	47.2 (41.2)	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Median [Min, Max]	28.0 [0, 181]	28.0 [0, 181]	35.0 [0, 184]	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Inattention Rating										
Mean (SD)	70.5 (50.1)	70.5 (50.1)	81.3 (53.9)	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Median [Min, Max]	61.0 [0, 223]	61.0 [0,223]	73.0 [0, 228]	n/a	n/a	n/a	n/a	n/a	n/a	n/a
Employment Status										
Not employed	1020 (24.4%)	1020 (24.4%)	1564 (18.8%)	907 (17.3%)	1228 (17.7%)	974 (16.2%)	806 (14.5%)	836 (13.8%)	607 (11.6%)	5358 (15.3%)
Employed	3167 (75.6%)	3167 (75.6%)	6774 (81.2%)	4336 (82.7%)	5712 (82.3%)	5055 (83.8%)	4742 (85.5%)	5226 (86.2%)	4634 (88.4%)	29705 (84.7%)
Weekly Pay (£)										
Mean (SD)	211 (453)	211 (453)	265 (428)	240 (355)	328 (1250)	387 (1110)	444 (560)	475 (1260)	549 (857)	399 (992)
Median [Min, Max]	180 [3.25, 21900]	180 [3.25, 21900]	218 [3.25, 21900]	200 [0, 9100]	250 [0, 52900]	300 [0, 53900]	375 [0, 22500]	385 [0,78100]	440 [0, 38500]	300 [0,78100]
Missing	1319 (31.5%)	1319 (31.5%)	2348 (28.2%)	1330 (25.4%)	1860 (26.8%)	1665 (27.6%)	1819 (32.8%)	1881 (31.0%)	1545 (29.5%)	10100 (28.8%)

2.5. *Identification assumptions*

The identification assumptions in our regression models are that the inattention and hyperactivity symptom scales are determined exogenously and adulthood labour market outcomes are endogenous. We have assumed that a causal relationship would occur indirectly where ADHD-related symptoms influence labour market outcomes through academic attainment and the development of key cognitive and non-cognitive skills (Cunha et al., 2010). We also assume that childhood ADHD-related symptoms could persist and have a direct negative impact of labour market performance during adulthood.

We have accounted for potential confounding by including several observed variables as independent variables in the regression models, for example father’s socioeconomic status (see section 2.2.3), and through inverse probability weighting (see Section 2.4.1). It is plausible that unobserved variables, such as disruption to children’s early environments, could explain some of the observed relationship between childhood ADHD-related symptoms and adulthood labour market performance, but we assume this to be insubstantial and unlikely to materially impact our findings.

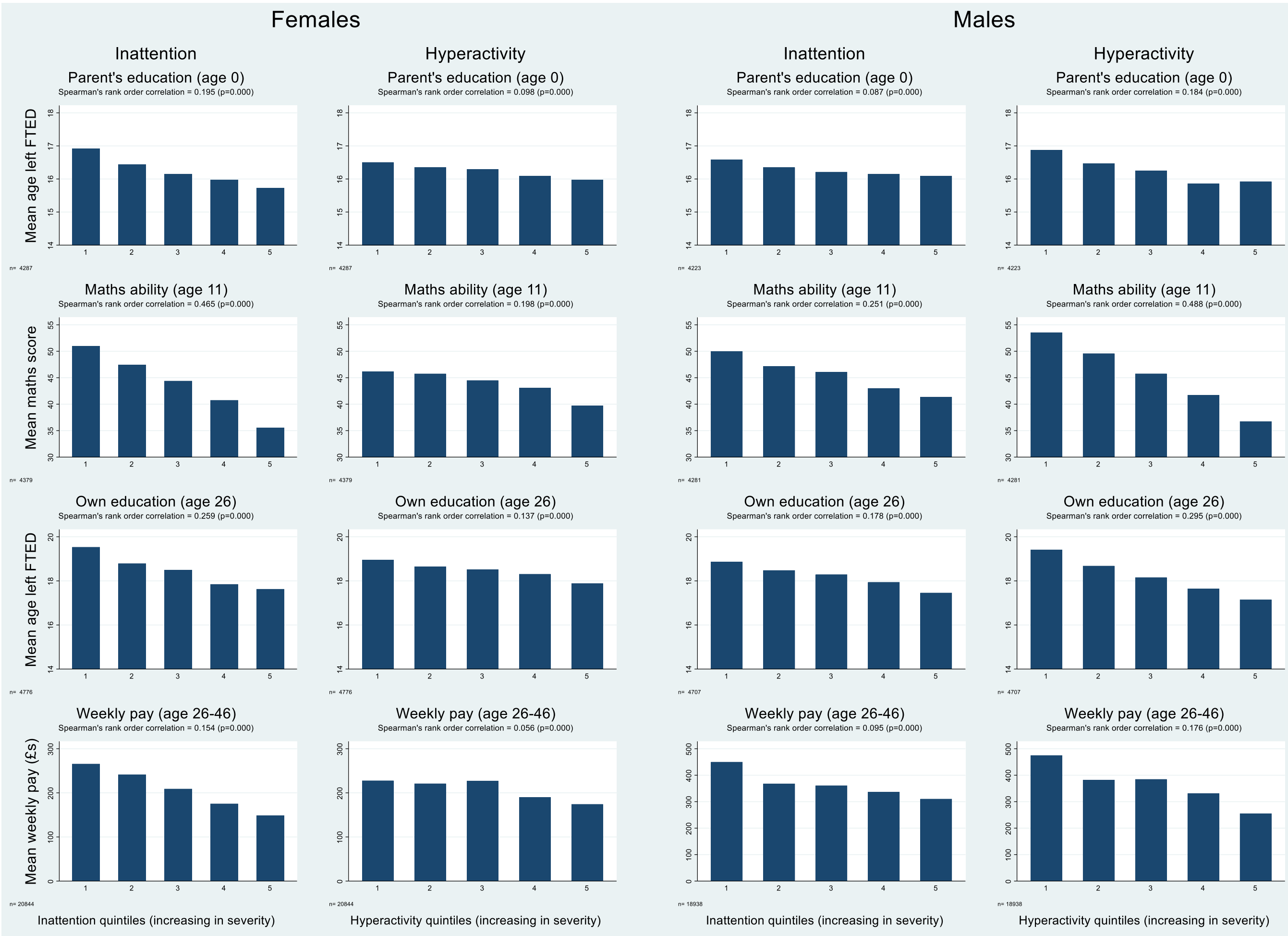

Fig. 2. Mean values of socioeconomic status (age 0), educational attainment (ages 10 and 26) and weekly pay (ages 26–46) by quintile of ADHD symptoms, split by ADHD symptom scale, gender and age. (Note that FTED refers to full-time education).

3. Results

3.1. Data preparation

Fig. 1 shows how the analysis sample is derived from the initial birth sample. The initial sample has 17,196 individuals. Participants are included in our main analysis if the ADHD-related symptoms are reported at age 10 (n = 11,295, 66%) and at least one earnings observation is recorded between ages 26 and 46.

In total there are 8338 individuals (n) and 35,063 observations (N) in the analysis sample (average of 4 observations per individual).

3.2. Descriptive statistics

Table 1 shows descriptive statistics for the time-invariant characteristics (Z_i), listed in chronological order, and time-varying characteristics (X_{it}), reported by age.

The age at which participants' mothers finished full time education are comparable for males and females. The mean and median maths scores (age 10) were slightly higher for males than females (mean 45.4 vs 43.8). The hyperactivity and inattention ratings (age 10) were also higher for males, indicating more severe symptoms. The mean age of leaving full time education was similar for males and females (18.2 vs 18.5 years) although the median was one year lower among males (16.0 vs 17.0). Holding a degree was more common among men than women (17.6% of men vs 15.7% of women). Missing values were most common in the mother's age of leaving education and the maths score variables (>7%). Data on the individual's post-16 educational attainment were more complete (<2% missing).

Employment increases from age 29 onwards, from 81.8% of respondents at age 29 to 87.8% at age 46. Weekly pay, conditional on employment, also increases with age from £ 237 at age 26 to £ 555 at age 46. The likelihood that participants are married or in a civil partnership increases from 30.3% at age 26 to 62.8% at age 42, and the likelihood that participants live in London decreases from 10.2% at age 29 to 7.0% at age 46.

3.3. Bivariate analyses

Fig. 2 shows the results of our bivariate analyses of inequalities in the distribution of key variables measured at birth, during childhood and early adulthood against the two ADHD symptom scales. All variables are unequally distributed across the ADHD symptom scales, with positive, statistically significant ($p < 0.05$) Spearman rank order correlations, indicating that people with more severe ADHD symptoms have lower socioeconomic status (age 0), lower cognitive skills (age 10) and lower education status (age 26). For both genders and both ADHD symptom scales, educational attainment (age 10 and 26) were more unequally distributed against ADHD symptoms than socioeconomic status (age 0) (e.g. for females, Spearman's rank order correlation was 0.195 for socioeconomic status, 0.465 for educational attainment at age 10, and 0.259 for educational attainment at age 26). For females, all three

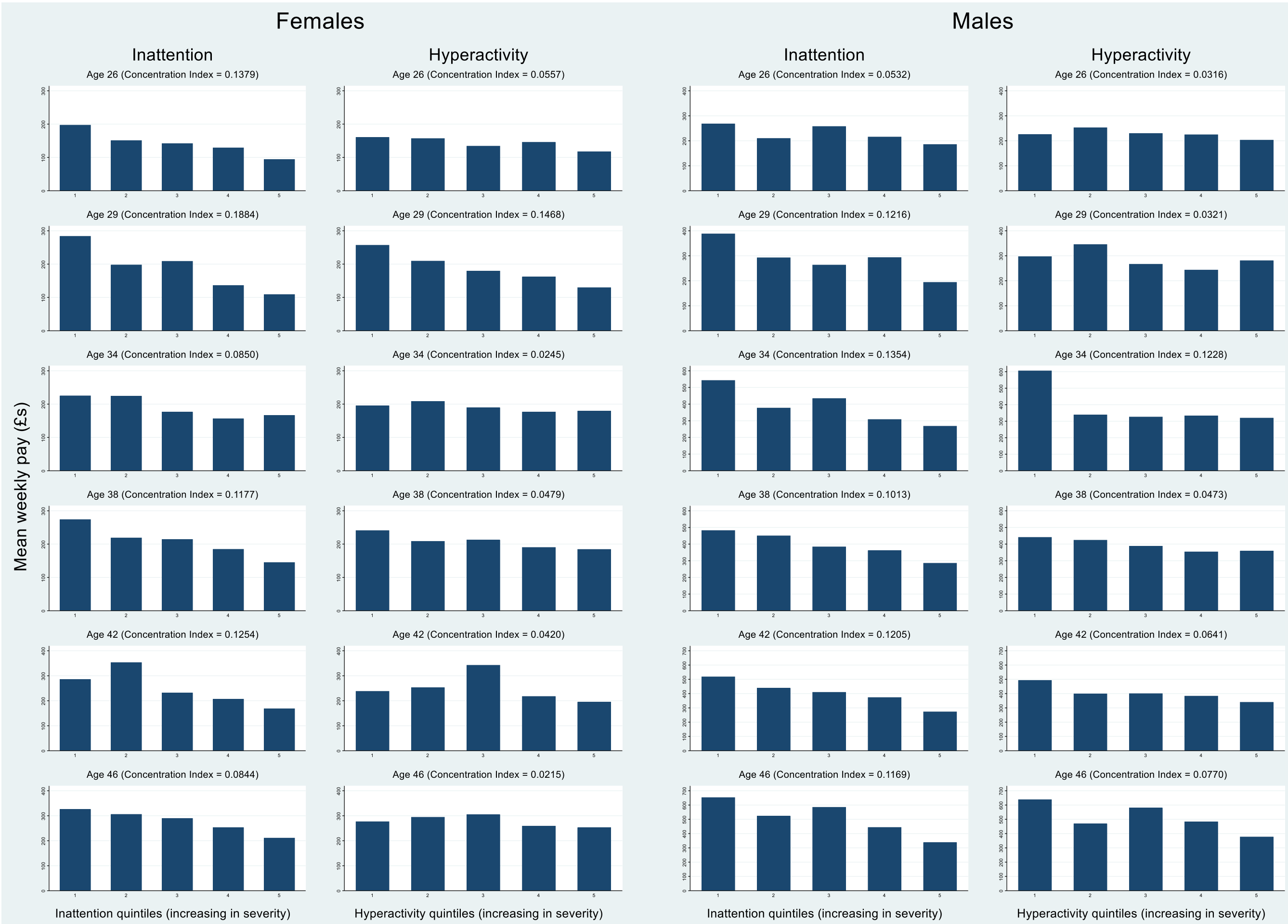

Fig. 3. Concentration index and mean values of weekly pay by quintile of ADHD symptoms, split by ADHD symptom scale, gender and age.

variables were more unevenly distributed against inattention symptoms than they were against hyperactivity symptoms; whereas for males, the variables were more unevenly distributed against hyperactivity symptoms than they were against inattention symptoms.

The Spearman's rank order correlation and concentration indices showed that weekly pay was also unequally distributed across both ADHD symptom scales, for both genders and at each timepoint (Figs. 2, 3 and A1). People with more severe ADHD symptoms had lower pay ($p < 0.05$). However, the Spearman's rank order correlation showed that, for both genders and both ADHD symptom scales, pay was more evenly distributed than were the socioeconomic and educational attainment variables measured during childhood and early adulthood. The concentration curves and indices additionally indicated that inequality in pay was larger when plotted against inattention than against hyperactivity, for both genders and all time points. There was no indication that these inequalities increased (or decreased) over time.

3.4. Regression analysis

3.4.1. Employment

Results are shown in Table 2 and visualisations are shown in Fig. 3. To address RQ1, both the inattention (model 1A) and hyperactivity (model 1B) ratings at age 10 show a statistically significant negative association with employment during adulthood in the unadjusted (OR 0.79 for inattention and 0.89 for hyperactivity) and fully adjusted models (OR 0.83 for inattention and 0.87 for hyperactivity). The average marginal effect estimate for the fully adjusted model indicates that a one standard deviation increase in the inattention and hyperactivity scales reduces employment by 1.8 percentage points and 1.3 percentage points respectively (this is equivalent to a 54.1 unit increase in the 230 point inattention scale and a 41.6 unit increase in the 184 point hyperactivity scale).

When compared to the unadjusted models (model i.), the addition of demographic variables (gender, marital status and region) leads to small increases in the estimated magnitude of the relationship between ADHD symptoms and employment for both the inattention (from OR 0.79 to OR 0.69) and the hyperactivity (from OR 0.89 to OR 0.79) models. Of these demographic variables, only female gender has a statistically significant impact on employment. Across all models, our estimates indicate that on average females were 11%-13% less likely than men to be in work.

To address RQ2, the addition of the measure of socioeconomic status at birth has only a negligible effect on the estimated magnitude of the relationship between ADHD symptoms and employment for both inattention (from OR 0.69 to OR 0.70) and hyperactivity (OR 0.79). The addition of educational attainment (age 10) has a much larger effect on the relationship between ADHD symptoms and employment for both the inattention (from OR 0.70 to OR 0.81) and the hyperactivity (from OR 0.79 to OR 0.86) models. In contrast, the addition of educational attainment (degree status at age 26) has only a small effect for both the inattention (from OR 0.81 to OR 0.83) and the hyperactivity (from OR 0.86 to 0.87) models. The model AIC indicates better model fit as each of the additional covariates are added.

A comparison of the average marginal effects associated with each model indicates that 43% (or 36%) of the relationship between an increased inattention (or hyperactivity) rating during childhood and decreased employment during adulthood is due to poorer performance

Table 2
Logistic regression models estimating the probability of employment.

Model 1A: Relationship between inattention (age 10) and employment during adulthood (ages 26–46)

	RQ1						RQ2								
	(i)			(ii)			(iii)			(iv)			(v)		
	Odds Ratios	*CI*	*p*	*Odds Ratios*	*CI*	*p*	*Odds Ratios*	*CI*	*p*	*Odds Ratios*	*CI*	*p*	*Odds Ratios*	*CI*	*p*
Intercept	8.37	7.88 – 8.88	< 0.001	65.99	53.56 – 81.31	< 0.001	32.31	20.47 – 50.98	< 0.001	11.60	7.13 – 18.88	< 0.001	16.03	9.75 – 26.35	< 0.001
Re-scaled inattention score	0.79	0.74 – 0.84	< 0.001	0.69	0.65 – 0.73	< 0.001	0.70	0.66 – 0.74	< 0.001	0.81	0.76 – 0.87	< 0.001	0.83	0.78 – 0.89	< 0.001
Gender				0.26	0.23 – 0.29	< 0.001	0.26	0.23 – 0.30	< 0.001	0.29	0.26 – 0.33	< 0.001	0.29	0.26 – 0.33	< 0.001
Living In London				0.95	0.80 – 1.13	0.568	0.94	0.79 – 1.11	0.447	0.94	0.79 – 1.11	0.471	0.91	0.76 – 1.08	0.277
Marital Status				1.05	0.97 – 1.15	0.240	1.05	0.96 – 1.15	0.243	1.04	0.95 – 1.13	0.397	1.02	0.93 – 1.11	0.724
Father's Age Of Leaving Education							1.05	1.02 – 1.07	0.001	1.02	0.99 – 1.04	0.208	1.00	0.98 – 1.03	0.914
Degree Status										1.03	1.02 – 1.04	< 0.001	1.03	1.02 – 1.03	< 0.001
Maths Score (Age 10)													1.55	1.37 – 1.75	< 0.001
n (individuals)	8338			8338			8338			8338			8338		
N (observations)	35063			35063			35063			35063			35063		
AIC	26210.536			25482.467			25468.818			25323.269			25268.110		
Average marginal effect (re-scaled inattention score)	−0.022	−0.028– − 0.017	< 0.001	−0.035	−0.041– − 0.030	< 0.001	−0.034	−0.040– − 0.029	< 0.001	−0.019	−0.025– − 0.010	< 0.001	−0.018	−0.024– − 0.011	< 0.001
Reduction in average marginal effect compared to model (ii)	n/a			n/a			2.9%			45.7%			48.6%		

Model 1B: Relationship between hyperactivity (age 10) and employment during adulthood (ages 26–46)

	RQ1						RQ2								
	(i)			(ii)			(iii)			(iv)			(v)		
	Odds Ratios	*CI*	*p*	*Odds Ratios*	*CI*	*p*	*Odds Ratios*	*CI*	*p*	*Odds Ratios*	*CI*	*p*	*Odds Ratios*	*CI*	*p*
Intercept	8.32	7.83 – 8.84	< 0.001	58.26	47.30 – 71.75	< 0.001	22.81	14.51 – 35.87	< 0.001	8.47	5.32 – 13.47	< 0.001	12.31	7.64 – 19.82	< 0.001
Re-scaled hyperactivity score	0.89	0.84 – 0.94	< 0.001	0.79	0.74 – 0.83	< 0.001	0.79	0.75 – 0.84	< 0.001	0.86	0.81 – 0.91	< 0.001	0.87	0.82 – 0.92	< 0.001
Gender				0.28	0.25 – 0.32	< 0.001	0.28	0.25 – 0.32	< 0.001	0.30	0.27 – 0.34	< 0.001	0.30	0.27 – 0.34	< 0.001
Living In London				0.98	0.83 – 1.17	0.849	0.96	0.81 – 1.14	0.645	0.95	0.80 – 1.13	0.570	0.92	0.77 – 1.09	0.337
Marital Status				1.07	0.98 – 1.17	0.146	1.07	0.98 – 1.17	0.154	1.04	0.95 – 1.14	0.387	1.02	0.93 – 1.11	0.732
Father's Age Of Leaving Education							1.06	1.03 – 1.09	< 0.001	1.02	0.99 – 1.04	0.184	1.00	0.98 – 1.03	0.898
Degree Status										1.04	1.03 – 1.04	< 0.001	1.03	1.02 – 1.04	< 0.001
Maths Score (Age 10)													1.58	1.39 – 1.78	< 0.001
n (individuals)	8338			8338			8338			8338			8338		
N (observations)	35063			35063			35063			35063			35063		
AIC	26275.044			25615.133			25588.950			25342.524			25282.048		
Average marginal effect (re-scaled hyperactivity score)	−0.011	−0.017– − 0.006	< 0.001	−0.022	−0.028– − 0.017	< 0.001	-0.022	−0.027– − 0.016	< 0.001	-0.014	−0.020– − 0.008	< 0.001	-0.013	−0.019– − 0.008	< 0.001
Reduction in average marginal effect compared to model (ii)	n/a			n/a			0.0%			36.4%			40.9%		

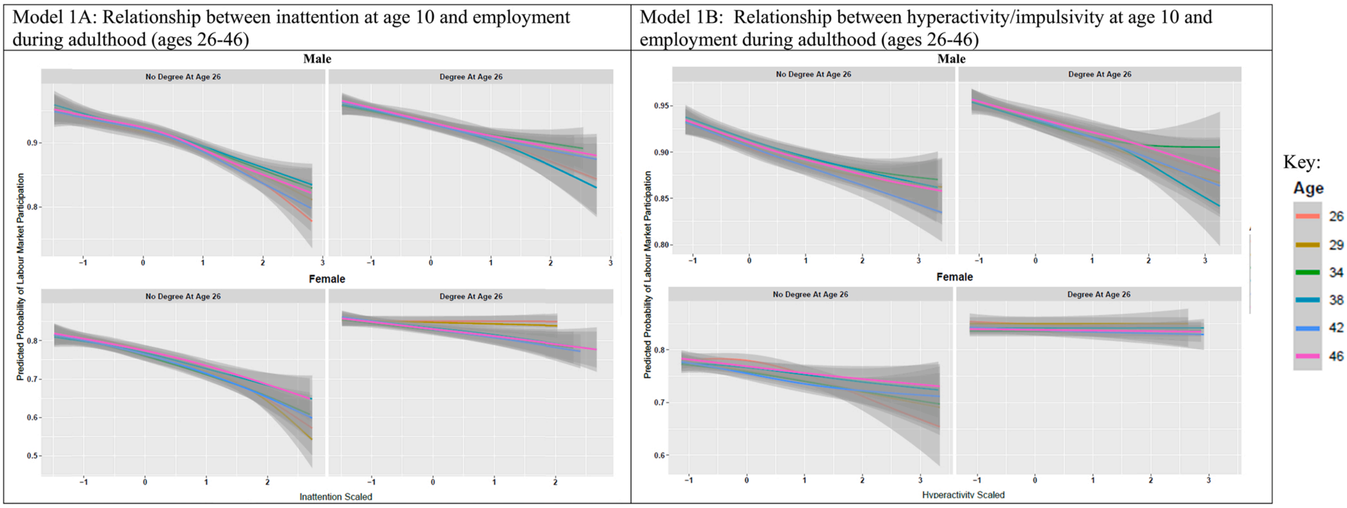

Fig. 4. Predicted probabilities of employment, by gender and degree status

at school during childhood. Differences in degree status account for only 3%– 5% of the relationship between ADHD symptoms and employment.

Fig. 4 shows that the negative association between ADHD symptoms and the probability of employment is consistent across each age point. For example, in males with degrees and average ADHD symptom domain score (i.e., 0), the distance between the probability of employment at age 26 and age 42 does not differ significantly. This distance remains within the 95% confidence interval for those with ADHD symptoms one standard deviation away from the mean.

3.4.2. Pay

Results are shown in Table 3 and the visualisations are shown in Fig. 5. To address RQ1, a statistically significant relationship between the inattention rating (model 2A) and pay, conditional on employment, is observed in the unadjusted and adjusted models. The average marginal effect estimate for the fully adjusted model indicates that a one standard deviation increase in the inattention rating is associated with a 2.6% reduction in pay. The relationship between the hyperactivity rating (model 2B) and pay tends to be of a smaller magnitude and is not statistically significant across all models.

Of the demographic variables (gender, marital status and region) included in the models, all have a statistically significant impact on pay. The average marginal effect estimate for the fully adjusted models indicates that, conditional on employment, females earn 55% less than men (models 2 A and 2 B). Those living in London (compared to other regions) and those with a degree (compared to those without a degree) reported pay that were 20% and 37% higher respectively.

To address RQ2, a comparison of the marginal effects associated with each model indicates that the addition of the measure of socioeconomic status at birth reduces the estimated magnitude of the relationship between the inattention or hyperactivity rating and pay by 10% and 18% respectively. The model R^2 indicates better model fit as each of the additional covariates are added. As with the employment regression model, it is differences in the cognitive ability measure (age 10) that account for a larger proportion (at least 50%) of the gradient between inattention or hyperactivity and labour market outcomes. In contrast, differences in degree status account for only 3%– 5% of the relationship between ADHD symptoms and pay.

Fig. 5 is similar to Fig. 4, in that differences between the ADHD symptom scales do not change by large amounts over time.

3.4.3. Inverse probability weighting (sensitivity analysis)

Results are shown in the appendix Tables A2 to A9. Tables A2–A5 show the regression models estimating the probability of employment (Eq. 2), and Tables A6–A9 show the regression models estimating pay (Eq. 3), for each ADHD symptom and each selected age (26 and 46). Comparisons of the coefficients of interest in column 1 (without survey weights) and column 2 (with survey weights) of each table show there is very little difference in the observed associations between ADHD symptom scales and labour market outcomes. For example, Table A2 shows regression results for the probability of employment at age 46. The inattention rating (age 10) is associated with a 2 percentage point reduction in the probability of employment for a one standard deviation change in the inattention rating before and after adding the survey weights from the IPW model. The associations and statistical significance of other covariates in the models are also mostly unaffected by the inclusion of survey weights.

4. Discussion and conclusion

4.1. Main findings

Addressing the first research question (RQ1), the regression models show that ADHD symptoms in childhood were negatively associated with employment and pay during adulthood. A one standard deviation increase in the inattention and hyperactivity scales significantly ($p < 0.001$) reduced employment by 1.8 percentage points and 1.3 percentage points respectively. A one standard deviation increase in inattention scales ($p < 0.001$) reduced pay (conditional on employment) by 2.6 percentage points. The negative association between hyperactivity symptoms and pay was not statistically significant.

The second research question (RQ2) explored why childhood ADHD symptoms are linked to poorer adulthood labour market outcomes. Our regression models indicate that differences in educational attainment (age 10) accounts for 40–50% of the observed relationships between ADHD symptoms and labour market outcomes. Differences in socioeconomic status at birth and educational attainment (degree status) at age 26 accounted for a much smaller proportion of the relationship. This is consistent with our bivariate analyses which identified small differences in socioeconomic status at birth, when ranked against ADHD symptoms, but larger inequalities in educational attainment (age 10 and 26) and labour market outcomes during adulthood.

Our sensitivity analyses (Appendix Tables A2-A9) indicate that sample attrition and non-response do not impact on the association between ADHD symptoms and people's labour market outcomes.

Table 3
Regression models estimating log weekly inflation-adjusted pay (£), conditional on employment.

Model 2A: Relationship between inattention (age 10) and log weekly, inflation-adjusted pay (£)

	RQ1						RQ2								
	(i)			(ii)			(iii)			(iv)			(v)		
	Estimates	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept	5.83	5.81 – 5.84	< 0.001	6.64	6.61 – 6.68	< 0.001	6.09	6.00 – 6.18	< 0.001	5.70	5.60 – 5.79	< 0.001	6.00	5.90 – 6.09	< 0.001
Re-scaled inattention score	-0.06	-0.07 – – 0.04	< 0.001	-0.11	-0.12 – – 0.10	< 0.001	-0.10	-0.11 – – 0.09	< 0.001	-0.04	-0.06 – – 0.03	< 0.001	-0.03	-0.04 – – 0.01	< 0.001
Gender				-0.60	-0.62 – – 0.58	< 0.001	-0.59	-0.62 – – 0.57	< 0.001	-0.55	-0.58 – – 0.53	< 0.001	-0.56	-0.58 – – 0.54	< 0.001
Living In London				0.21	0.17 – 0.24	< 0.001	0.19	0.16 – 0.23	< 0.001	0.19	0.16 – 0.23	< 0.001	0.17	0.14 – 0.20	< 0.001
Marital Status				0.14	0.13 – 0.16	< 0.001	0.14	0.13 – 0.16	< 0.001	0.14	0.12 – 0.15	< 0.001	0.12	0.10 – 0.13	< 0.001
Father's Age Of Leaving Education							0.03	0.03 – 0.04	< 0.001	0.02	0.02 – 0.03	< 0.001	0.01	0.01 – 0.02	< 0.001
Degree Status										0.01	0.01 – 0.01	< 0.001	0.01	0.01 – 0.01	< 0.001
Maths Score (Age 10)													0.37	0.34 – 0.39	< 0.001
n (individuals)	7286			7286			7286			7286			7286		
N (observations)	24944			24944			24944			24944			24944		
R^2	0.006			0.183			0.196			0.218			0.263		
Average marginal effect (re-scaled inattention score)	-0.057	-0.071- – 0.043	< 0.001	-0.111	-0.124- – 0.099	< 0.001	-0.099	-0.011- – 0.088	< 0.001	-0.044	-0.058- – 0.031	< 0.001	-0.026	-0.039- – 0.013	< 0.001
Reduction in average marginal effect compared to model (ii)	n/a			n/a			10.8%			60.3%			76.6%		

Model 2B: Relationship between hyperactivity (age 10) and log weekly, inflation-adjusted pay (£)

	RQ1						RQ2								
	(i)			(ii)			(iii)			(iv)			(v)		
	Estimates	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*	*Estimates*	*CI*	*p*
Intercept	5.83	5.81 – 5.84	< 0.001	6.60	6.56 – 6.64	< 0.001	5.97	5.89 – 6.06	< 0.001	5.60	5.51 – 5.69	< 0.001	5.93	5.84 – 6.02	< 0.001
Re-scaled hyperactivity score	0.00	-0.01 – 0.02	0.871	-0.04	-0.06 – – 0.03	< 0.001	-0.04	-0.05 – – 0.03	< 0.001	-0.01	-0.02 – 0.00	0.145	-0.00	-0.01 – 0.01	0.940
Gender				-0.57	-0.59 – – 0.55	< 0.001	-0.57	-0.59 – – 0.54	< 0.001	-0.54	-0.56 – – 0.51	< 0.001	-0.55	-0.57 – – 0.53	< 0.001
Living In London				0.21	0.18 – 0.25	< 0.001	0.20	0.16 – 0.23	< 0.001	0.20	0.16 – 0.23	< 0.001	0.17	0.14 – 0.20	< 0.001
Marital Status				0.15	0.13 – 0.17	< 0.001	0.15	0.13 – 0.17	< 0.001	0.14	0.12 – 0.16	< 0.001	0.12	0.10 – 0.13	< 0.001
Father's Age Of Leaving Education							0.04	0.03 – 0.04	< 0.001	0.02	0.02 – 0.03	< 0.001	0.01	0.01 – 0.02	< 0.001
Degree Status										0.01	0.01 – 0.01	< 0.001	0.01	0.01 – 0.01	< 0.001
Maths Score (Age 10)													0.37	0.35 – 0.39	< 0.001
n (individuals)	7286			7286			7286			7286			7286		
N (observations)	24944			24944			24944			24944			24944		
R^2	0.000			0.164			0.181			0.215			0.261		
Average marginal effect (re-scaled hyperactivity score)	-0.001	-0.013 – 0.015	0.871	-0.044	-0.056 - – 0.031	<0.001	-0.036	-0.050- – 0.025	<0.001	-0.009	-0.021- – 0.003	0.145	-0.000	-0.011–0.011	0.940
Average marginal effect (re-scaled hyperactivity score)	n/a			n/a			18.2%			79.5%			100%		

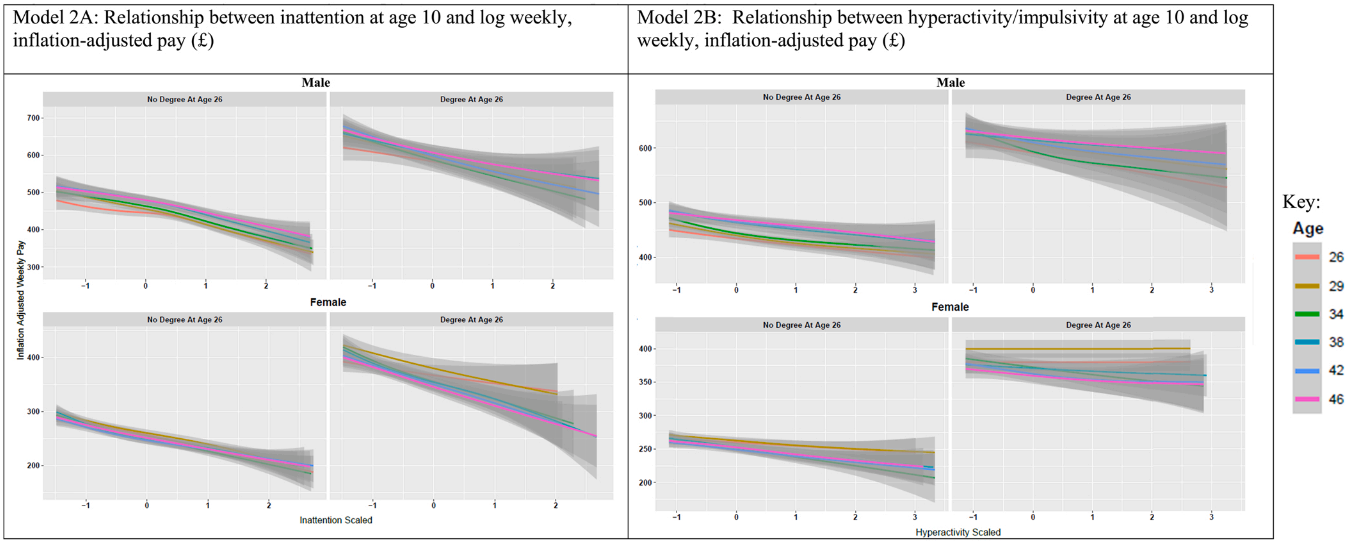

Fig. 5. Predicted weekly inflation-adjusted pay (£), conditional on employment, by gender and degree status

4.2. Comparison with previous literature

Our results are consistent with two systematic reviews (Gordon et al., 2019; Christiansen et al., 2021) which included 19 longitudinal studies (reported in 35 articles) of childhood ADHD and labour market outcomes from 7 countries. The probability of not being employed was higher for people living with ADHD versus controls in 12 of the 14 studies that assessed employment status. Childhood ADHD was also linked to lower skilled work in seven of eight studies, and negatively impacted gross earnings in one study (Gordon et al., 2019; Christiansen et al., 2021).

These reviews identified limited evidence on the impacts of ADHD in the UK (2 studies) or other European (3 studies) labour markets. Knapp et al. (2011), who similarly utilised data from the BCS, identified negative associations between ADHD symptoms and adulthood labour market outcomes at a single time point (age 30). Our study extends this work by separately assessing the relationship with hyperactivity and inattention symptoms, and by including longitudinal labour market outcomes at ages 26, 30, 34, 38, 42 and 46.

Our study further adds to the literature by measuring symptoms on two continuous scales. A key strength of this approach is that we capture labour market outcomes among individuals who are undiagnosed or have sub-threshold ADHD. Another strength is that we are able to assess granular details about the severity of ADHD symptoms that would not be possible using a binary (yes/no) measure of diagnosis. This enabled us to assess dose-response relationships (as illustrated in Figs. 4 and 5).

4.2.1. Differential impacts of inattention and hyperactivity

To our knowledge, this is the first study to analyse the separate impact of childhood inattention and hyperactivity symptoms on adulthood labour market outcomes. We find that inattention symptoms had a more substantial impact on employment and were significantly associated with reduced pay whereas hyperactivity symptoms were not.

Inattention and hyperactivity symptoms may differently impact on labour market outcomes due to variations in effect pathways. Inattention is thought to play a role in early academic attainment and in the development of cognitive skills such as executive function and non-cognitive skills including engagement, motivation, and organization, whereas this is less likely to be the case with hyperactivity (Martel et al., 2007). This may explain findings by Salla et al. (2016) who observed significant impacts of inattention but not hyperactivity on educational outcomes during adolescence.

Labour market outcomes may also be impacted directly by ADHD symptoms that persist through adulthood (Gordon et al., 2019). Our regression models suggest that the observed relationships between ADHD symptoms and labour market outcomes remain even after adjusting for socioeconomic status at birth, cognitive ability (age 10) and degree status (age 26). Inattention symptoms may frequently persist into adulthood, whereas symptoms of hyperactivity appear more likely to naturally decline as children mature (Wilens et al., 2010). Equally, inattention may influence personality characteristics that determine workplace success, for example difficulties with perseverance and premeditation can make people more prone to quitting jobs (Gordon et al., 2019).

4.3. Policy implications

The link between childhood ADHD and labour market outcomes has typically been explained through the indirect negative impact of ADHD on educational attainment (Gordon et al., 2019). Our findings indicate the indirect relationship may be mediated by early childhood cognition, which explained a much larger variation in labour market outcomes than degree status. This indicates the potential value of novel interventions to address cognitive inequalities during childhood to support people with ADHD-related symptoms and allow them to realise their full potential in the labour market later in life. As with other early interventions, the greatest benefits are likely to be achieved in children from the most disadvantaged backgrounds (Doyle et al., 2009; Cunha et al., 2021).

Pharmacotherapy and psychological therapy are currently recommended treatment options for children in the UK with an ADHD diagnosis (NICE, 2018). Our findings suggest that treatment may have large returns on investment in the labour market if they are effective in mediating the relationship with childhood ADHD symptoms. The BCS does not collect information on ADHD treatment provision, and therefore we could not evaluate the impact of intervention directly. The current literature indicates little effect of stimulant medication on education outcomes, but this evidence is limited to three observational studies which are at a risk of bias, not least because the most severe

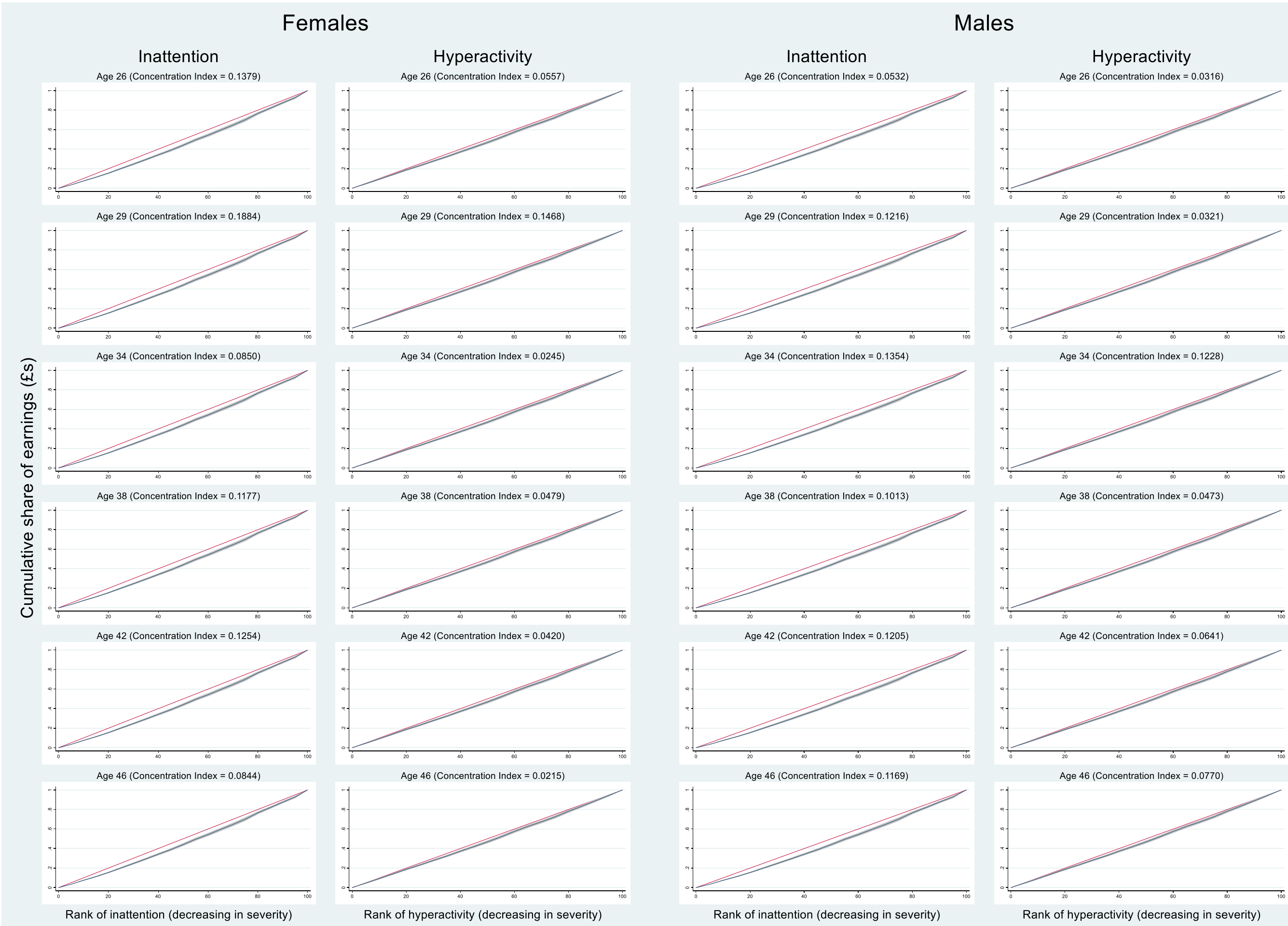

Fig. A1. Concentration curves and concentration index for weekly pay against rank of ADHD symptoms, split by ADHD symptom scale, gender and age. Red line indicates line of equality. Grey area indicates 95% confidence interval.

ADHD cases are more likely to be prescribed medication (Gordon et al., 2019). We are not aware of any studies which directly evaluate the impact of treatment on labour market outcomes and this should be a key direction for future research.

4.4. Strengths, limitations, and future research

A strength of our study is the use of the BCS which enabled us to generate continuous scales of ADHD-related symptoms, rather than rely on clinical diagnoses which may represent only the most extreme cases (Asherson et al., 2012) and exclude children from certain socioeconomic groups. Further strengths of the dataset include the large sample size and long follow up period allowing us to assess employment outcomes from ages 26 to 46. As a result, and in contrast to other longitudinal panel datasets, our measures of childhood health and education status are not compromised by recall bias.

The data also allows us to adjust for father's education, a proxy for socioeconomic circumstances. We measure father's education at birth as this is the most crucial period for parental investment in children's later human capital production (Cunha et al., 2021). Other parental characteristics, such as mental health status, are also potential confounders, but were not included as independent variables in our regression analysis to avoid overspecification. We consider the omission of such variables unlikely to substantially influence the estimated coefficients for ADHD symptoms.

The use of childhood symptom scores instead of an ADHD diagnosis allowed us to compare the separate impact of inattention and hyperactivity. However, our conclusions may be limited as the stronger association between labour market outcomes and inattention might be due to the inattention scale being a stronger proxy for ADHD diagnosis than the hyperactivity scale. In addition, the generalisability of our findings may be questioned, given that childhood symptoms were measured in the 1980s when ADHD was viewed primarily as an inattention disorder. As with all longitudinal studies conducted from childhood through to adulthood, our findings may be affected by healthcare, technological and societal changes that have occurred since the study conception. However, the external validity of our findings may be supported by more recent evidence in the 2010s which continue to find detrimental impacts of ADHD diagnoses on school outcomes (Fleming et al., 2017).

A further limitation is our reliance on self-reported employment outcomes, which may be subject to measurement error. As indicated by Moore et al. (2000), there is a general tendency to modestly under report income and labour market activity in survey data. Hence it is possible that we underestimate the association between ADHD symptoms and labour market performance. This interpretation is, however, dependent on underreporting occurring proportionally across the population, and we do not know whether the accuracy of self-report differs amongst people with and without ADHD symptoms. Future research might link participants' employment records from Government sources (e.g. HMRC data) to provide a more accurate record of employment. In addition, we measured educational attainment based on degree status as a binary variable. It may be that ADHD is more strongly associated with performance on secondary education outcomes (e.g. GSCEs or A-levels) or achievement in different types of further education.

Finally, our study observed how people with more severe ADHD symptoms perform less well in the labour market, in terms of employment and pay. We did not assess the relationship between ADHD symptoms and employment preferences. People with ADHD symptoms may have skills and prefer jobs which happen to pay less. For instance, people with ADHD are more likely to have entrepreneurial intentions (Rajah et al., 2021) and be self-employed (Patel et al., 2021) than people without ADHD. Patel et al. (2021) suggests that self-employment may explain 59% of the negative relationship between ADHD symptoms and earnings. Further, it may be a conscious decision for some individuals to work fewer hours, or not to work at all, to maximise their quality of life. An important question for future research is to determine the degree to which these apparently negative outcomes affect people's quality of life, why people with ADHD make the labour market decisions they do, and the extent to which it is desirable that policy makers focus on equalising labour market outcomes for people with and without ADHD. Perhaps policy interventions ought to focus instead on supporting people to make choices that support their overall quality of life, and on ensuring that workplaces can accommodate their needs.

Data Availability

Data will be made available on request.

Acknowledgements

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Appendix

See Fig. A1 and Tables A1-A9 here.

Table A1
Variables used to construct ADHD Symptom Scales.

Inattention	Hyperactivity / Impulsivity
Cannot concentrate on particular task (Range 1–47)	Excitable/impulsive (Range 1–47)
Easily Distracted (Range 1–47)	Shows restless or overactive behavior (Range 1–47)
Pays attention in class (Negatively scored with range 1–47	Squirmy and fidgety (Range 1–47)
Fails to finish tasks (Range 1–47)	Interferes with others (Range 1–47)
Shows perseverance (Negatively scored with range 1–47)	

Table A2
Linear probability models estimating relationships between inattention and the probability of employment, with and without survey weights, age 46.

	Linear Probability Model	Survey Weighted Linear Probability Model
Intercept	0.95***	0.95***
	[0.92, 0.98]	[0.92, 0.98]
Inattention Rating (Scaled)	-0.02***	-0.02***
	[− 0.03, − 0.01]	[− 0.03, − 0.01]
Sex	-0.07***	-0.07***
	[− 0.09, − 0.05]	[− 0.09, − 0.05]
Region (Lives In London)	-0.03	-0.03
	[− 0.07, 0.00]	[− 0.07, 0.01]
Marital Status	0.06***	0.06***
	[0.04, 0.07]	[0.04, 0.08]
Father's Age Of Leaving Education (Scaled)	-0.01	-0.01*
	[− 0.02, 0.00]	[− 0.02, − 0.00]
Degree Status	0.02*	0.02*
	[0.00, 0.04]	[0.00, 0.04]
Math Score At Age 10 (Scaled)	0.02***	0.02***
	[0.01, 0.03]	[0.01, 0.03]
N	4970	4970
R2	0.04	0.04

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table A3
Linear probability models estimating relationships between hyperactivity and the probability of employment, with and without survey weights, age 46.

	Linear Probability Model	Survey Weighted Linear Probability Model
Intercept	0.95***	0.94***
	[0.92, 0.98]	[0.91, 0.98]
Hyperactivity Rating (Scaled)	-0.02***	-0.02***
	[− 0.03, − 0.01]	[− 0.03, − 0.01]
Sex	-0.07***	-0.07***
	[− 0.09, − 0.05]	[− 0.09, − 0.05]
Region (Lives In London)	-0.03	-0.03
	[− 0.07, 0.00]	[− 0.07, 0.01]
Marital Status	0.06***	0.06***
	[0.04, 0.07]	[0.04, 0.08]
Father's Age Of Leaving Education (Scaled)	-0.01	-0.01*
	[− 0.02, 0.00]	[− 0.02, − 0.00]
Degree Status	0.03*	0.03**
	[0.01, 0.05]	[0.01, 0.04]
Math Score At Age 10 (Scaled)	0.03***	0.03***
	[0.02, 0.04]	[0.02, 0.04]
N	4970	4970
R2	0.04	0.04

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table A4
Linear probability models estimating relationships between inattention and pay, with and without survey weights, age 46.

	OLS Model	Survey Weighted Linear Model
Intercept	6.88***	6.88***
	[6.80, 6.96]	[6.79, 6.96]
Inattention Rating (Scaled)	-0.03*	-0.03*
	[− 0.06, − 0.01]	[− 0.05, − 0.00]
Sex	-0.62***	-0.63***
	[− 0.67, − 0.58]	[− 0.67, − 0.58]
Region (Lives In London)	0.18***	0.16*
	[0.08, 0.27]	[0.01, 0.31]
Marital Status	0.04	0.05*
	[− 0.01, 0.09]	[0.00, 0.10]
Father's Age Of Leaving Education (Scaled)	0.04***	0.04*
	[0.02, 0.07]	[0.01, 0.07]
Degree Status	0.30***	0.29***
	[0.24, 0.35]	[0.24, 0.35]
Math Score At Age 10 (Scaled)	0.09***	0.09***
	[0.06, 0.12]	[0.06, 0.12]
N	3519	3519
R2	0.25	0.24

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table A5
Linear probability models estimating relationships between hyperactivity and pay, with and without survey weights, age 46.

	OLS Model	Survey Weighted Linear Model
Intercept	6.86***	6.86***
	[6.77, 6.94]	[6.77, 6.94]
Hyperactivity Rating (Scaled)	0.00	0.00
	[− 0.02, 0.03]	[− 0.02, 0.03]
Sex	-0.61***	-0.61***
	[− 0.66, − 0.56]	[− 0.66, − 0.57]
Region (Lives In London)	0.18***	0.16*
	[0.08, 0.27]	[0.01, 0.32]
Marital Status	0.04	0.06*
	[− 0.01, 0.09]	[0.01, 0.10]
Father's Age Of Leaving Education (Scaled)	0.04***	0.04*
	[0.02, 0.07]	[0.01, 0.08]
Degree Status	0.30***	0.30***
	[0.25, 0.35]	[0.24, 0.35]
Math Score At Age 10 (Scaled)	0.10***	0.11***
	[0.08, 0.13]	[0.08, 0.14]
N	3519	3519
R2	0.24	0.24

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table A6
Linear probability models estimating relationships between inattention and the probability of employment, with and without survey weights, age 26.

	Linear Probability Model	Survey Weighted Linear Probability Model
Intercept	0.97***	0.98***
	[0.93, 1.00]	[0.95, 1.01]
Inattention Rating (Scaled)	-0.03***	-0.03***
	[− 0.04, − 0.02]	[− 0.05, − 0.02]
Sex	-0.09***	-0.10***
	[− 0.11, − 0.07]	[− 0.12, − 0.08]
Region (Lives In London)	-0.01	-0.01
	[− 0.05, 0.02]	[− 0.05, 0.02]
Marital Status	-0.00	-0.00
	[− 0.03, 0.02]	[− 0.02, 0.02]
Father's Age Of Leaving Education (Scaled)	-0.00	-0.01
	[− 0.01, 0.01]	[− 0.02, 0.00]
Degree Status	0.00	-0.00
	[− 0.03, 0.03]	[− 0.03, 0.03]
Math Score At Age 10 (Scaled)	0.03***	0.03***
	[0.02, 0.05]	[0.02, 0.05]
N	5005	5005
R2	0.03	0.04

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table A7
Linear probability models estimating relationships between hyperactivity and the probability of employment, with and without survey weights, age 26.

	Linear Probability Model	Survey Weighted Linear Probability Model
Intercept	0.96***	0.97***
	[0.92, 0.99]	[0.94, 1.00]
Hyperactivity Rating (Scaled)	-0.02***	-0.02***
	[– 0.03, – 0.01]	[– 0.03, – 0.01]
Sex	-0.08***	-0.09***
	[– 0.11, – 0.06]	[– 0.11, – 0.07]
Region (Lives In London)	-0.01	-0.01
	[– 0.04, 0.02]	[– 0.04, 0.02]
Marital Status	-0.00	-0.00
	[– 0.03, 0.02]	[– 0.02, 0.02]
Father's Age Of Leaving Education (Scaled)	-0.00	-0.01
	[– 0.02, 0.01]	[– 0.02, 0.00]
Degree Status	0.01	0.01
	[– 0.02, 0.04]	[– 0.02, 0.03]
Math Score At Age 10 (Scaled)	0.04***	0.04***
	[0.03, 0.05]	[0.03, 0.05]
N	5005	5005
R2	0.03	0.03

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table A8
Linear probability models estimating relationships between inattention and pay, with and without survey weights, age 26.

	OLS	Survey Weighted Linear Model
Intercept	6.03***	6.03***
	[5.97, 6.08]	[5.97, 6.08]
Inattention Rating (Scaled)	-0.03**	-0.03**
	[– 0.05, – 0.01]	[– 0.05, – 0.01]
Sex	-0.34***	-0.34***
	[– 0.38, – 0.31]	[– 0.38, – 0.31]
Region (Lives In London)	0.22***	0.23***
	[0.17, 0.28]	[0.17, 0.29]
Marital Status	-0.02	-0.01
	[– 0.05, 0.02]	[– 0.05, 0.03]
Father's Age Of Leaving Education (Scaled)	0.03**	0.02*
	[0.01, 0.05]	[0.00, 0.04]
Degree Status	0.19***	0.19***
	[0.14, 0.24]	[0.15, 0.24]
Math Score At Age 10 (Scaled)	0.07***	0.07***
	[0.05, 0.09]	[0.05, 0.09]
N	3740	3740
R2	0.17	0.17

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

Table A9
Linear probability models estimating relationships between hyperactivity and pay, with and without survey weights, age 26.

	OLS	Survey Weighted Linear Model
Intercept	6.01***	6.01***
	[5.96, 6.07]	[5.95, 6.07]
Hyperactivity Rating (Scaled)	-0.01	-0.01
	[– 0.03, 0.00]	[– 0.03, 0.01]
Sex	-0.33***	-0.33***
	[– 0.37, – 0.30]	[– 0.37, – 0.30]
Region (Lives In London)	0.22***	0.23***
	[0.17, 0.28]	[0.17, 0.29]
Marital Status	-0.02	-0.01
	[– 0.05, 0.02]	[– 0.05, 0.03]
Father's Age Of Leaving Education (Scaled)	0.03**	0.02**
	[0.01, 0.04]	[0.00, 0.04]
Degree Status	0.19***	0.20***
	[0.15, 0.24]	[0.15, 0.25]
Math Score At Age 10 (Scaled)	0.08***	0.08***
	[0.06, 0.10]	[0.06, 0.10]
N	3740	3740
R2	0.17	0.17

*** $p < 0.001$; ** $p < 0.01$; * $p < 0.05$.

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