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ABSTRACT

The Gender Wage Gap across Life: Effects of Genetic Predisposition Towards Higher Educational Attainment*

Using two polygenic scores (PGS) for educational attainment in a biomedical study of all those born in a single week in Great Britain in 1958 we show that the genetic predisposition for educational attainment is associated with labour market participation and wages over the life- course for men and women. Those with a higher PGS spend more time in employment and full-time employment and, when in employment, earn higher hourly wages. The employment associations are more pronounced for women than for men. Conditional on employment, the PGS wage associations are sizeable, persistent and similar for men and women between ages 33 and 55. A one standard deviation increase in the PGS is associated with a 6-10 log point increase in hourly earnings. However, whereas a 1 standard deviation increase in the PGS at age 23 raises women's earnings by around 5 log points, it is not statistically significant among men. These associations are robust to non-random selection into employment and to controls for parental education. Our results suggest that genetic endowments of a cohort born a half century ago continued to play a significant role in their fortunes in the labor market of the 21st Century.

JEL Classification: I26, J31, J16, J24

Keywords: gender wage gap, employment, educational attainment, polygenic score, National Child Development Study

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1. Introduction

For over half a century, social scientists have argued that educational attainment is a major determinant of individuals' success in the labor market. It is an investment individuals make in their skills which determines their value to the employer, and thus their wage (Becker, 1964). It sits alongside other components of what Becker termed "human capital" such as experience and tenure in the canonical Mincerian wage equation (Mincer, 1958). Others have emphasized the value of qualifications in signaling a job seeker's type to employers who have limited information about the relative quality of job applicants (Arrow, 1973; Spence, 1973). Both the human capital and signaling theories predict those with higher qualifications have greater chances of obtaining high-skilled jobs offering higher wage returns. A vast literature in labour economics offers substantial empirical support for this proposition (Goldin and Katz, 2008).

In the genetic sciences, evidence has been emerging for some time for a genetic component to educational attainment. Twin studies have suggested moderate-high heritability of around 40% (Silventoinen et al., 2020) and adoption studies also find evidence for both genetic and environmental influences on education attainment (Halpern-Manners et al., 2020). Recent research finds that polygenic scores (PGSs) derived from Genome-Wide Association Studies (GWAS) account for around 12-16 percent of the variance in educational attainment (Okbay et al, 2022). By virtue of random genetic segregation, there should be no mean differences in the PGS by sex, that is, the PGS should be evenly distributed between women and men across the 'autosomes' (the chromosomes shared by both genders upon which GWAS are typically carried out). Yet, for much of the post-War period men had higher educational attainment than women, likely due to societal expectations regarding gendered roles, with women undertaking the bulk of caring responsibilities in the home whilst men entered the labour market to fulfil their role as 'breadwinners' (Becker, 1985).

In a two-person household faced with two tasks – market and home production – this sexual division of labour could be viewed as an efficient allocation of household resources (Becker, 1985). This specialization of tasks by sex in turn created incentives for men to invest in human capital and for women to limit their labour market experience, resulting in a gender gap in hourly earnings driven in part by sex differences in human capital. However, among recent birth cohorts, women have closed the gap in educational attainment and are increasing their work experience relative to men such that, in human capital terms, women are becoming “more like men” (Goldin, 2014). In recent studies, decompositions of the gender wage gap indicate the gap is only partially explained by sex differences in human capital (Blau and Kahn, 2017). Much of the gap is unexplained.

This unexplained gap might arise if women’s wage returns to education were lower than those for men, but the empirical literature suggests this is not the case (Psacharopoulos and Patrinos, 2018). It could also reflect preferences for occupations with high non-wage amenities, or differences in job search behaviour (Cortes et al., 2022). It may also reflect employer discrimination against women on grounds of taste (Becker, 1957) or statistical discrimination by which employers who, faced with a lack of precise information regarding the productivity of individual women, may infer their productivity based on what they expect the average productivity of women to be (Phelps, 1972). There are therefore a number of reasons as to why women’s wage returns to a genetic predisposition for educational attainment may be lower than those for men such that their natural abilities are not rewarded in the same way as men in the labour market.

If women face lower wage returns for their educational attainment, this may lower their incentives to invest in their human capital in the first place (Adda et al., 2017). This, coupled with persistent societal expectations regarding men’s and women’s roles at work and in the home, might mean that the correlation between the PGS and actual educational attainment will be smaller for women than it is for men. If women face discrimination in the labor market, and if women derive greater utility from home production than men due to the congruence of that role with societal expectations, women may be more likely to enter employment where their potential earnings in employment are high, such that we might anticipate greater positive selection into employment by women relative to men. The implication is that the PGS for educational attainment may be a stronger predictor of employment and full-time employment among women than it is among men.

We test the association between the genetic predisposition for educational attainment and gaps in men and women’s employment and earnings using data from the National Child Development

Study (NCDS), which tracks all those born in a single week in Great Britain in 1958 throughout their life. In this paper we track NCDS participants until they are aged 55 in 2013. We match participants' work histories which enable us to identify cohort members' employment and earnings over time to data on two parameterizations of a PGS for educational attainment obtained from a biomedical study conducted when cohort participants were aged 44.

We show that those with a higher PGS spend more time in employment, especially full-time employment and, when in employment, earn higher hourly wages. The employment associations are more pronounced for women than for men. Between the ages of 20 and 55, a one standard deviation increase in the PGS is associated with a half a percentage point increase in the time spent in employment among men, but the effect is four-times greater in the case of women (a 2.3 percentage point increase). The PGS is not significantly associated with men's time in full-time employment but among women the association is large and statistically significant. A one standard deviation increase in women's PGS leads to a 3-percentage point increase in their full-time employment.

Examining the association between the PGS for educational attainment and employment at each survey sweep we find the correlation between the PGS and employment probabilities among women is largest in their early 20s, diminishing but remaining significant in their 30s and, in the case of full-time employment, into their 40s. The greater association with the PGS on women's employment probabilities in their 20s and 30s, when they were most fertile, is consistent with the proposition that women in this birth cohort attached higher value to time out of paid work earlier in their lives, such that only those with high earnings potential selected into employment.

Conditional on employment, the PGS wage associations are sizeable, persistent, and similar for men and women between ages 33 and 55. A one standard deviation increase in the PGS is associated with a 6-10 log point increase in hourly earnings. However, a one standard deviation increase in the PGS at age 23 raises women's earnings by around 5 log points, compared to a statistically non-significant 1 log point among men. These wage associations are robust to non-random selection into employment and to controls for parental education.

We therefore confirm the proposition that those with a higher genetic predisposition for educational attainment have greater attachment to the labor market. This is the case for both men and women, but the effect is greater among women and, in the case of full-time employment, is confined to women. The fact that the association is larger for women is consistent with the proposition that women face greater out-of-work utility – potentially linked to societal expectations regarding caring responsibilities in the home – such that they require greater rewards from the labor market to enter and remain in employment.

We also confirm the proposition that a higher genetic predisposition for educational attainment is associated with higher earnings for both men and women. However, contrary to the literature on gender discrimination, we find no evidence of lower returns to the educational attainment PGS for women compared with men. Instead, returns are very similar across sex and, if anything, a little larger for women early in life.

2. Literature and hypotheses

In the UK, as elsewhere, there has been gradual convergence in the gender wage gap in recent decades, including some closure in the gap across birth cohorts (Bryson et al., 2020) but a substantial gap remains (Kunze, 2018). In the past, sex differences in work experience and educational attainment explained a large component of the gap, but these gaps have closed over time (what Goldin (2014) refers to as the "grand gender convergence") such that most of the gap today is unexplained, in the sense that it is not accounted for by substantial differences in human capital. It remains the case that differences in higher education specialisms (notably the relative paucity of women engaged in STEM degrees) contribute to a gender wage gap among graduates, but career returns to STEM graduation appear to be lower for women than for men (White and Smith, 2022). Differences in work experience also persist, many of them associated with fertility decisions, such that women – particularly mothers – have a much higher probability of working part-time than their male counterparts and spend considerably longer than their partners out of the labour market for child-related reasons (Bryson et al., 2020). Time out of the labor market can result in the depletion of acquired human capital, whilst time in part-time employment can even result in a wage penalty (Joshi et al., 2021). These differences in fertility-related work experience helps explain variance in the size of the gender wage gap over the life-course, which follows a hump-shape, peaking when workers are in their 40s (Joshi et al., 2021).

Whilst, traditionally, the unexplained or residual component of the gender wage gap was attributed to discrimination in the labor market, the residual may also reflect other unobserved sex differences which can impact earnings, such as tastes for competition, risk-taking and bargaining – although these are thought to contribute relatively little to gender wage differences (Blau and Kahn, 2017). Nevertheless, discrimination on the part of employers remains a distinct possibility. Some quasi-experimental studies suggest it may play some role in hiring (Goldin and Rouse, 2000), but pooled meta-analysis of correspondence studies finds a slightly higher probability for female candidates receiving positive responses to an application (Lippens et al., 2023). But the differential impact of new parenthood on mothers' and fathers' earnings – with women suffering a substantial wage penalty whilst men see a wage premium – is consistent with the proposition that employers may discriminate statistically against new mothers by questioning their commitment to employment, whilst doing precisely the opposite in the case of new fathers (Yu and Hara, 2021). That said, some of this gender gap in earnings among new parents may also reflect occupational downgrading or decisions to work fewer hours – or avoid long-hours working - on returning to work. The additional utility women may derive from non-wage components of the job, such as flexible hours schedules, may come at the expense of earnings, consistent with the theory of compensating wage differentials (Goldin, 2014).

Motherhood, or the prospect that young women may become mothers, is not the only reason for a gender wage gap. The wages of women remain lower than men's on labor market entry, and a wage penalty attaches to women relative to 'like' men even among those who never go on to have children (Joshi et al., 2021).

Although the genetic predisposition for educational attainment has not featured in the gender wage gap literature to date, the PGS for educational attainment can shed light on the nature of the gender wage gap in various ways. PGS are measures of genetic predisposition towards traits, calculated using the counts of an individual's alleles (0,1,2) at specific locations in the genome and the population-weighted estimate of the association between that allele and the outcome. By virtue of random genetic segregation, there should exist no mean differences in PGS between women and men as alleles on the autosomes are inherited randomly irrespective of sex. Causal effects from DNA to wages or employment (however they may manifest or be biologically mediated) are also expected to be consistent. Therefore, differential PGS associations with outcomes among women and men may be taken as indicative of sex-specific social or environmental factors (barriers). However, it is uncertain, a priori, whether the earnings return to the PGS will vary by sex and, if so, whether this varies over time.

We hypothesise that the PGS for educational attainment will be positively associated with the probability of employment and time in employment (Hypothesis 1). This is because the value of working relative to not working (and the value of working longer hours in full-time employment) is greatest for those with the highest earnings potential (Willis, 1986). We further hypothesize that associations between the PGS and employment may be greater in the case of women (Hypothesis 2) because, as shown in earlier work which imputed earnings to non-participants in the NCDS and its 1970 counterpart, the British Cohort Study (BCS), women were more positively selected into employment than men on their potential earnings (Neuberger et al., 2011).

Whilst we anticipate positive selection into (full-time) employment based on higher PGS scores, this may vary over the life-course in ways that differ by sex due to differences in the value of outside options (Hypothesis 3). Positive selection into employment among women will be most pronounced during child-rearing years due to the increased value women attach to time out of the labor market at that point in their lives. Similar findings are presented by Bryson et al. (2020) who also used the imputed earnings approach deployed by Neuberger et al (2011) and found that positive selection of women into employment in the NCDS was only apparent through to age 42, roughly corresponding to the period in which women were often engaged in childcaring responsibilities.

We anticipate that a higher score on the educational attainment PGS will also be associated with higher earnings over the life-course for men and women (Hypothesis 4). That is because a higher PGS captures factors which impact worker productivity and thus earnings, both directly through educational attainment and indirectly, for instance, if a higher PGS is correlated with higher ability and thus lowers the cost of effort (Prendergast, 1999; Lazear, 2000).

However, we anticipate the PGS association with earnings may be attenuated somewhat in the case of women (Hypothesis 5). This might be the case if women are less likely to acquire commensurate educational qualifications (eg. due to societal expectations governing women's investments in the home and the labor market) or because women anticipate labor market discrimination and thus anticipate lower returns to investment in education.

3. Data and Estimation

Our data are from the National Child Development Study (NCDS), a longitudinal cohort study of all those born in a single week in March 1958 (https://cls.ucl.ac.uk/cls-studies/1958-national-child-development-study/). Our estimates draw on data from nine sweeps at ages 7, 11, 16, 23, 33, 42, 44, 50, 55, together with data collected at birth. We omit analyses of the age 46 sweep, which was a telephone survey, and the age 62 follow up in 2020 to avoid COVID-related issues.

Our estimation sample is confined to those providing valid biological data in the Biomedical Survey conducted in 2002/2003 when cohort members were aged 44 to 45.[1] Therefore, individuals must be a respondent to the Biomedical Survey and provide genetic data sufficient to produce the PGS. Of the 17,416[2] individuals initially identified for inclusion in the study, 1,286 were dead and 1,236 had emigrated by the time the Biomedical Survey was conducted in 2002. 6,312 provided valid PGS data, that is 39 per cent of the remaining 16,036 sample. Issues relating to sample attrition and non-response are discussed in Section 3.3. For further information on the genotyping, imputation and quality control of the NCDS see Appendix one.

3.1: Time in Employment and Full-time Employment

We begin by estimating Ordinary Least Squares models where our dependent variable is the proportion of time the cohort member has spent in employment between ages 20 and 55. These models are run on the 5,908 individuals (2,913 men and 2,995 women) who had a valid PGS for

[1] More information about the biomedical data can be found at https://cls.ucl.ac.uk/cls-studies/1958-national-child-development-study/ncds-age-44-biomedical-sweep/

[2] Although 18,558 were originally identified for inclusion in the Perinatal Mortality Study (PMS), as it was originally designated, 1,142 were not included in the study.

educational attainment and provided work history data. Among this sample, 78 percent of men and 82 percent of women had responded to 8 or all 9 of the interviews sweeps between ages 7 and 55.

The model takes the following form:

$$E_i = \alpha_i + \beta_1 ZPGS_i + \beta_{2\ldots21} PC1_i \ldots PC20_i + \beta_{22} Missing_i + \varepsilon_i \qquad \text{(Equation 1)}$$

where E_i is the proportion of time a cohort member was in employment between ages 20 and 55. This is calculated as the number of years in which the cohort member's main activity was paid employment divided by the number of years in which the cohort member's employment status was known.

$ZPGS_i$ is a standardized version of the polygenic score (PGS) for educational attainment for each individual cohort member. It has a mean of zero and standard deviation of one. The PGS was derived from the largest GWAS of educational attainment to date (Okbay et al., 2022). Details are provided in Appendix One. We also derived a more restrictive PGS to use in analyses as PGS robustness checks. β_1 captures the correlation between the PGS and time in employment such that we can estimate the change in employment associated with a one standard deviation shift in the PGS. PC1..PC20 represent the first 20 principal components of the inferred genetic structure in the NCDS and are included to minimize the likelihood of residual population stratification bias on our results.[3]

$Missing_i$ captures the number of years in which employment status for an individual Cohort member is missing in the data due either to non-response for a particular survey sweep or because some work history data was missing for a given sweep. The mean number of years for which employment status was missing was 1.4 years in the case of men and 1.8 years for women.

[3] Population stratification refers to a type of confounding bias that can induce relationships between genetics and observed traits at the population level. Broad differences in historical ancestry (e.g., allele frequencies) are observed between population groups driven by geographic and physical boundaries that restricted between-group mating, and subsequent genetic drift over time. Where traits developed differently amongst these population groups, they may appear spuriously related to genetics despite no causal relationship (Novembre et al., 2008).

In a variant of equation (1) we condition on parental education, captured by whether the cohort member's mother and father respectively left school at compulsory school leaving age, or whether they stayed on for longer. We condition on parental education given the possibility that indirect genetic effects may inflate our PGS associations (Morris et al., 2020). The effects that we are interested in are 'direct' genetic effects, i.e. the link between a cohort member's PGS and their labour market fortunes that arises due to the putative effect of their PGS. However, because genes are shared between the cohort member and their parents, indirect genetic effects can arise if the shared genes have an impact on their parents' education, which in turn impacts the cohort member's home environment, for example through parenting. We use parental education as a proxy for indirect genetic effects given that the NCDS did not measure parental genetics. These direct effects differ in magnitude across traits but have been consistently observed for every trait studied (Howe et al., 2022).

We run similar models replacing time in employment with time spent in full-time employment between ages 20 and 55.

To establish whether there is time-variance in the association between participation in employment and the PGS for educational attainment we supplement these models with linear estimation models estimating the probability of being in (a) employment (b) full-time employment at each interview sweep between ages 23 and 55. These models are similar to equation (1) but they are weighted to account for sample attrition by sex and sweep using the weights described below in Section 3.3. (They do not incorporate work history variables so do not include a variable capturing the amount of missingness in the work history data).

3.2: Earnings Models

The focal point for the analyses is pooled and separate-sex earnings equations run for separate survey years when respondents are aged 23, 33, 42, 50 and 55. The ordinary least squares earnings model specifications take the following form:

$$\text{Log}(W)_{it} = \alpha_i + \beta_1 PGS_i + \beta_{2\ldots21} PC1_i \ldots PC20_i + \varepsilon_i \qquad \text{(Equation 2)}$$

where W_{it} is log hourly earnings of individual i in survey t. Gross hourly earnings are derived from those in employment by dividing their reported last or usual gross earnings, and the pay period to which they relate, by usual hours worked per week, including any paid overtime. These wages were deflated by the retail price index to January 2000 prices.

The standardized PGS score discussed in Section 3.1 above captures the correlation between the PGS and log hourly earnings such that we can estimate the change in log hourly earnings associated with a one standard deviation shift in the PGS. In the pooled regressions the PGS score is interacted with a dummy variable identifying female cohort members.

As with the employment equations discussed in Section 3.1, the PGS score sits alongside 20 dummy variables which are the principal components of the genetic structure and, in a variant of equation (2) we condition on parental education, captured by whether the cohort member's mother and father respectively left school at compulsory school leaving age, or whether they stayed on for longer.

Throughout we drop outliers in the earnings distribution (those above 99th percentile and those below the bottom percentile of the hourly earnings distribution) and all estimates are weighted with attrition weights which are discussed in Section 3.3.

These models are supplemented by similar estimates which also incorporate the imputed earnings for the unemployed, those who are economically inactive, the self-employed and employees with missing hours or wage data. These estimates account for differential probabilities of employment across sex and over time such that the gender wage gaps reflect the gaps that would exist in the absence of non-random sex-based selection into employment. The models run with imputed earnings include a dummy variable identifying respondents with imputed earnings (where 1=imputed earnings, 0 otherwise). The procedure for imputing those earnings is detailed in Appendix Two.

3.3: Sample Attrition and Non-response

Our estimation sample is confined to those providing valid biometric data. Therefore, individuals must be a respondent to the biomedical survey and provide genetic data sufficient to produce the

PGS. Of the 17,416[4] individuals initially identified for inclusion in the study, 1,286 were dead and 1,236 had emigrated by the time the Biomedical Survey was conducted in 2002. 6,312 provided valid PGS data, that is 39 per cent of the remaining 16,036 sample.

Attrition is particularly problematic if it is systematically related to a key data item of interest. A common finding in social survey research, including that using the British birth cohorts, is that those from lower social classes, and thus lower earnings potential, are more likely to die prematurely (Fluharty et al., 2021) or attrit (Hawkes and Plewis, 2006). This implies that those with attributes leading to higher (lower) earnings – including the PGS score – are more (less) likely to be surveyed over time.

In examining this issue, we first considered the correlation between the standardized PGS score for educational attainment and the number of survey sweeps cohort members were present. Between birth and age 55 there were eleven survey sweeps – at birth then at ages 7, 11, 16, 23, 33, 42, 44, 46, 50 and 55. Among those with a valid PGS, half (49.8%) were present in all 11 sweeps and three-quarters (77%) were present in at least 10 sweeps. Those with a higher PGS were present in more survey sweeps. In an Ordinary Least Squares regression containing the PGS score and its principal components, where the dependent variable was the number of sweeps cohort members were present, the coefficient for the standardized PGS is .10 (t-stat 7.13). However, this correlation was not significantly different by sex (the interaction term in a pooled sex regression is -.01 (t-stat 0.44). There was also no statistically significant difference between cohort members' PGS and their sex in predicting response to any given wave. Second, we examined whether sample attrition resulted in a sex differential in the PGS. At no sweep was there a statistically significant sex difference in the mean PGS. So, it seems that PGS scores were associated with the probability of responding to survey sweeps, but there was no difference in this propensity by sex and there were no mean differences in the PGS by sex at any point in the survey.

If panel attrition is correlated with factors that also determine earnings and may be correlated with sex, estimates of sex differences in earnings may be impacted by panel attrition across sweeps.

[4] Although 18,558 were originally identified for inclusion in the Perinatal Mortality Study (PMS), as it was originally designated, 1,142 were not included in the study.

Therefore, we construct a sample attrition weight for each survey sweep. This entails running a probit equation for the probability of responding to that sweep, recovering the probability of response for each cohort member (having dropped those cases who were never part of the Perinatal Mortality Study or had died or emigrated), then taking the inverse of that probability as a survey weight which is used subsequently in running earnings equations. These models contain covariates collected at birth (sex, race, region of residence, birthweight, months breastfed, father's social class) and in childhood (Southgate reading test score at age 7, Bristol Social Adjustment Guide score at age 7, mathematics score at age 11, Rutter scale score at age 16). We add dummy variables identifying item non-response on categorical variables and, if there is item non-response on a continuous variable, we impute the mean value and incorporate a dummy variable identifying cases with imputed values. These models account for between 4 and 7 percent of the variance in responses to individual survey sweeps. The full models are presented in Appendix Table A4 in Appendix Three.

4. Results

We begin with estimates of the association between the PGS for educational attainment and employment and full-time employment before turning to the association between the PGS and earnings.

4.1: Time in Employment and Full-time Employment

In this section we present models estimating the correlation between cohort members' PGS and the time they spent in employment and in full-time employment between age 20 and age 55, followed by models estimating the correlation between their PGS score and whether they were in employment when a survey sweep was conducted at ages 23, 33, 42, 50 and 55.

4.1.1: Percentage of Time in Employment and Full-Time Employment between ages 20 and 55

Between the ages of 20 and 55 men had spent 93 percent of their time in employment, nearly all of which (90 percent) was in full-time employment. In comparison, women had spent 77 percent of their time in employment, only half (49 percent) of which was in full-time employment.

Table 1 presents the OLS estimates for time spent in employment (Panel A) and full-time employment (Panel B) between ages 20 and 55 as per equation (1). Models are presented for men and women separately. The PGS is positively correlated with time in employment among both men and women, consistent with Hypothesis 1. Among men a one standard deviation increase in the PGS is associated with a 0.5 percentage point increase in employment. Among women it is associated with a 2.3 percentage point increase. This difference in the association between men and women is statistically significant; in a model pooling both sexes, the interaction between the PGS and being female has a coefficient of 0.018 and a t-statistic of 3.47.

Controlling for parental education in columns 2 and 4 of Table 1, as indicated by whether the cohort member's mother and father stayed on at school beyond compulsory education, makes little difference to the PGS coefficient. While this does not rule out indirect effects of the PGS on cohort members' employment, it provides support for a direct effect of the PGS on the propensity for employment in so far as those indirect effects operate via parental education. The results are therefore consistent with the proposition in Hypothesis 2 that a higher PGS increases the returns to employment, especially among women.

Table 1 Panel B provides no strong support that the PGS is associated with the percentage of time men spend in full-time employment, but does indicate a positive, statistically significant association with the time women spend in full-time employment. (Again, the male-female difference is statistically significant: the interaction between the PGS and a female dummy has a coefficient of 0.030 and a t-statistic of 4.59). A one standard deviation increase in the PGS is associated with a 3-percentage point increase in women's full-time employment. On the assumption – which we test below – that a higher PGS denotes higher earnings potential, this suggests that women are positively selected into full-time employment in a way that men are not – at least in this birth cohort. Once again, these results were not sensitive to the inclusion of parental education.

Results are virtually identical when we rerun estimates with our robustness PGS.[5]

[5] Models using our variant PGS are available on request.

4.1.2: The Probability of Employment and Full-Time Employment At Survey Interview

The analysis above established a correlation between the PGS for educational attainment and the time cohort members spent in employment and full-time employment between ages 20 and 55. However, as discussed in Section Two, we anticipate men's and women's employment status to vary across the life-cycle due to family formation and its implications for the household division of labor. These differences are apparent in Figure 1 which depicts the employment and full-time employment rates for men and women in the estimation sample across their lifetimes. In the left-hand panel it is apparent that men's employment rates rise through to their mid-30s, after which they plateau before declining from their late 40s. Women's employment rates are below those of men across the whole life-course. This employment gap opens markedly in their 20s when women's employment rates fall while men's rise. Women's employment rates then rise throughout their 30s and 40s, peaking at roughly the same age as men's before declining from their late 40s. In the right-hand panel of Figure 1 we see men's full-time employment mirrors their overall employment pattern because so few work part-time. By contrast, among women, full-time employment rates peak in their teens, only to decline through to their early 30s. They then begin to recover somewhat, but they never approach the full-time employment rates of teenage girls such that, by age 50, only around half the women in the study are working full-time, compared with nearly 90 percent of men.

The marked divergence in employment and full-time employment rates between men and women across the life cycle is consistent with differences in the utility men and women derive from paid work versus time out of the labor market at various junctures in their lives. Women of fertile age often face intermittent employment during childrearing years and, if they do return to work, often do so on a part-time basis (Kleven et al., 2024; Bryson et al., 2020). If women derive greater utility from being out of paid work at that time in their lives, compared with men, we expect those women remaining in employment at that time to be more positively selected into employment in terms of their earnings potential as compared with men. The implication is that the correlation between one's PGS for educational attainment and employment will be stronger when women are in their 20s and 30s compared with later in life, a pattern we would not expect to see among men whose labor supply is impacted less by family formation. These differences should be particularly pronounced for full-time employment since working full-time is likely to be less compatible with work-life balance in the presence of children.

Table 2 shows the correlation between the PGS for educational attainment and the propensity for employment and full-time employment by sex and interview sweep. Panels A and B indicate that the PGS is not statistically significantly associated with men's propensity for employment or full-time employment at any of the survey interviews across the life-course. By contrast, Panel C shows women with a higher PGS for educational attainment are more likely to be in employment at age 23 and 33 relative to women with a lower PGS, with the effect being particularly pronounced at age 23. This is also apparent for full-time employment though, in this case, there is also a statistically significant, albeit smaller, correlation through to age 42 (Panel D). These results are consistent with the proposition underpinning Hypothesis 3 that a genetic predisposition for higher educational attainment and thus higher earning potential induces positive selection into employment – and particularly full-time employment – for women of fertile age but is not significant for men.[6]

4.2: Earnings

In this section we run ordinary least squares regressions with log hourly earnings as the dependent variable to establish what association, if any, the PGS for educational attainment has on the size of the gender wage gap. But first we estimate the raw gender wage gap by running regressions containing a female dummy variable and no other regressors for each interview sweep. In Panel A of Table 3 we report the gender wage gap for those in employment with a valid hourly wage. The gap is substantial at age 23 (16 log points) but doubles to 34 log points by the time cohort members reach their early-30s. It rises once more to 40 log points by age 42 before declining to 30 log points at age 55. These estimates are similar in magnitude and pattern to those reported at median hourly earnings for the same cohort in Bryson et al. (2020), and at the log of mean hourly

[6] These results are robust to controls for parental education and to the use of the variant PGS. In alternative models we included self-employment alongside employment in our definition of paid work. These models confirm the significance of the PGS in inducing women to enter paid work and full-time paid work among women, but this time the associations are statistically significant through to age 55, with the largest effects apparent at age 23, then age 33. However, they also revealed positive correlations between men's PGS for educational attainment and their propensity for paid work and full-time paid work at ages 33, 42 and 50, although the coefficients are smaller than those for women.

earnings (Joshi et al., 2021). Both the size and pattern in the gap are similar in Panel B of Table 3 when we also incorporate imputed earnings using the technique described in Appendix Twp. The inclusion of those with imputed earnings increases the gender wage gap at age 23 by around 4 log points, but differences in the female coefficient in Panels B and A after age 23 are small, consistent with stronger positive selection of women into employment in their early 20s but a much weaker effect thereafter.

Table 4 shows the correlation between the standardized PGS for educational attainment and log hourly earnings at each survey sweep as per equation (2), first for men in Panel A, then for women in Panel B and for the pooled sample of men and women in Panel C. Consistent with Hypothesis 4, the PGS is associated with higher earnings for men and women. Among men, a one standard deviation increase in the PGS raises earnings by 9 to 13 log points between ages 33 and 55. The correlation is much smaller and statistically non-significant at age 23. Among women in Panel B, the effects are similar between ages 42 and 55, but are 5 log points larger than those for men at ages 23 and 33, a difference that the interactions in the pooled sex models in Panel C confirm are statistically significant. This finding of a larger effect of the PGS for women than men in their 20s and 30s is not consistent with the proposition in Hypothesis 5 that the PGS effects might be attenuated in the case of women.

Table 5 reruns the analyses in Table 4, but this time incorporates cohort members with imputed earnings. The pattern of results for men in Panel A is similar to those in Table 4 with the standardized PGS raising men's earnings between ages 33 and 55, although the size of the effects is a little lower than in Table 4 (a one standard deviation increase in the PGS being associated with an hourly earnings increase of 6-10 log points). Among women the association between the PGS and log hourly earnings is positive and statistically significant across all years. As in the case of men, the size of the effects is a little lower than in Table 4, with a one standard deviation increase in the PGS resulting in earnings increases of 5-10 log points. The association is greater for women than it is for men at age 23 only, as indicated by the interaction effects in Panel C.

5. Discussion and Conclusions

Ours is the first paper to examine the association between the genetic propensity for educational attainment measured with a polygenic score (PGS) and gender gaps in employment and earnings. We do so for a birth cohort born in 1958, examining the association between a PGS collected in a biometric study when cohort members were aged 44, and their employment between ages 20 and 55, and earnings between age 23 and 55.

As anticipated, a higher PGS for educational attainment increased the time spent in employment across the life-course for both men and women, with the effect being four-times larger for women than for men. Furthermore, the effect was even more pronounced for full-time employment in the case of women – a one standard deviation higher PGS was associated with a 3-percentage point increase in time in full-time employment between ages 20 and 55 – whereas the PGS was not associated with men's full-time employment probabilities. When we examined time-variance in these effects across the life-course, we found the PGS correlations with employment and full-time employment among women were largest in their 20s and 30s. These results are consistent with the proposition that women were positively selected into employment based on their potential earnings during years of fertility when their utility outside of work would have been highest.

A higher PGS for educational attainment was associated with higher hourly earnings for both men and women between the ages of 33 and 55. A one standard deviation higher PGS was associated with an increase of around 9-14 log points in hourly earnings. However, among 23-year-olds, the PGS was only significantly associated with hourly earnings among women, not men. The size of these effects did not differ significantly for men and women aged 33 to 55, but PGS effects were larger for women than men aged 23 and 33 (by around 5 log points for a one standard deviation increase in the PGS). The broad pattern of results was similar when we included those with imputed earnings to account for differential effects of non-random selection into employment. Although the inclusion of those with imputed earnings reduced the size of the PGS effects somewhat, they remained large and statistically significant for women across the whole life course, and among men at all ages except age 23. Thus, there is no evidence that women faced lower returns to their genetic predisposition for educational attainment than their male counterparts.

The genetic predisposition for educational attainment captured in the PGS provides useful insights into the labor market experiences of men and women in this cohort. First, it indicates that gender gaps in employment – especially gaps in full-time employment – are narrower in this birth cohort among those with a higher genetic disposition for educational attainment. Although there are no differences by the PGS across men and women at the mean, women's labor market participation is more responsive to having higher earnings potential, especially earlier in life. Second, the higher earnings potential implied by a higher PGS for educational attainment is translated into higher earnings for both men and women across the life course. However, this responsiveness is somewhat larger earlier in their careers for women, resulting in a closure in the raw gender wage gap equivalent to a 5-log point reduction for an increase in one standard deviation in the PGS. This is equivalent to a closure of roughly one-third of the raw gender wage gap among employees, or a quarter of the raw gender wage gap when computed for employees and those with imputed earnings.

Recall that members of this birth cohort were first entering the labor market in the early 1970s if they left education at compulsory school leaving age, or the early 1980s if they were among the relatively small number who went on to higher education. Although today's labor market is rather different and the genetic disposition for educational attainment may have quite different effects on labor market participation and earnings among newer birth cohorts, the large positive association between the PGS for educational attainment and hourly earnings persisted in this birth cohort until age 55 in 2013, suggesting that genetic endowments of those born over a half a century earlier continued to play a significant role in the labor market fortunes of workers in the labor market of the 21st Century.

It is possible that our results are influenced by indirect genetic effects. Previous studies using genotype data from family members have shown that indirect effects vary but are larger for social traits (Howe et al, 2022). Given that the NCDS did not measure parental genotypes and there were insufficient sibling samples, we are unable to directly test the presence or magnitude of indirect genetic effects. We therefore used a measure of parental education as a proxy for indirect genetic effects in a supplementary analysis given that we expect indirect effects of a PGS for education to operate principally through parental education. While our approach cannot conclusively reject the presence of indirect genetic effects, our results suggest that these are likely to be small in as much as they are captured by parental education.

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Table 1: % Time in Employment Age 20-55				
	Men	**Men**	**Women**	**Women**
Panel A: All Employment				
Standardized PGS	0.005+	0.006*	0.023*	0.023*
	(1.84)	(2.07)	(5.21)	(5.09)
Parental Education	No	Yes	No	Yes
Adj R-sq	0.019	0.019	0.011	0.012
Panel B: Full-time Employment				
Standardized PGS	0.004	0.005+	0.033*	0.030*
	(1.29)	(1.65)	(5.73)	(5.20)
Parental Education	No	Yes	No	Yes
Adj R-sq	0.013	0.014	0.020	0.023
Unweighted N	2913	2913	2995	2995
Notes: (1) T-stats in parentheses (2) Significance: + p<0.10 * p<0.05 (3) All models contain 20 principal components of the PGS and a count variable for the number of missing years of work history.				

Table 2: Employment and Full-time Employment at Survey Sweeps					
	23	**33**	**42**	**50**	**55**
Panel A: All Employment, Men					
Standardized PGS	0.003	0.003	0.006	0.008	0.002
	(0.40)	(0.33)	(0.69)	(0.87)	(0.17)
Adj R-sq	0.008	0.005	0.010	0.008	0.010
Panel B: Full-time Employment, Men					
Standardized PGS	0.001	0.002	0.005	0.004	-0.011
	(0.17)	(0.20)	(0.60)	(0.46)	(1.10)
Adj R-sq	0.007	0.004	0.009	0.006	0.010
Panel C: All Employment, Women					
Standardized PGS	0.070*	0.028*	0.012	0.013+	-0.000
	(7.89)	(3.04)	(1.42)	(1.61)	(0.00)
Adj R-sq	0.028	0.012	0.005	0.008	0.007
Panel D: Full-time Employment, Women					
Standardized PGS	0.075*	0.055*	0.022*	0.016+	0.007
	(8.21)	(6.28)	(2.51)	(1.70)	(0.71)
Adj R-sq	0.029	0.025	0.011	0.007	0.008
Unweighted N, Men	2,691	2,765	3,037	2,733	2,556
Unweighted N, Women	2,797	2,897	3,080	2,822	2,687

Notes: (1) T-stats in parentheses (2) Significance: + p<0.10 * p<0.05 (3) All models contain 20 principal components of the PGS and are weighted to account for attrition.

Table 3: Raw Gender Gap in Log Hourly Earnings at Survey Sweeps					
	23	**33**	**42**	**50**	**55**
Panel A: Employees With a Valid Hourly Wage					
Female	-0.157*	-0.336*	-0.396*	-0.329*	-0.304*
	(22.93)	(28.51)	(27.47)	(24.56)	(19.76)
R-sq	0.07	0.11	0.10	0.10	0.08
Panel B: Including Imputed Earnings					
Female	-0.198*	-0.345*	-0.389*	-0.345*	-0.307*
	(34.87)	(37.50)	(33.83)	(32.41)	(25.95)
R-sq	0.13	0.14	0.11	0.11	0.08
Unweighted N, Panel A	7,528	6,588	7,001	5,901	4,819
Unweighted N, Panel B	11,693	10,839	10,981	9,386	8,501
Notes: (1) T-stats in parentheses (2) Significance: + p<0.10 * p<0.05 (3) Regressions are weighted with attrition weights. (4) Panel B models incorporate a dummy variable identifying those with imputed earnings.					

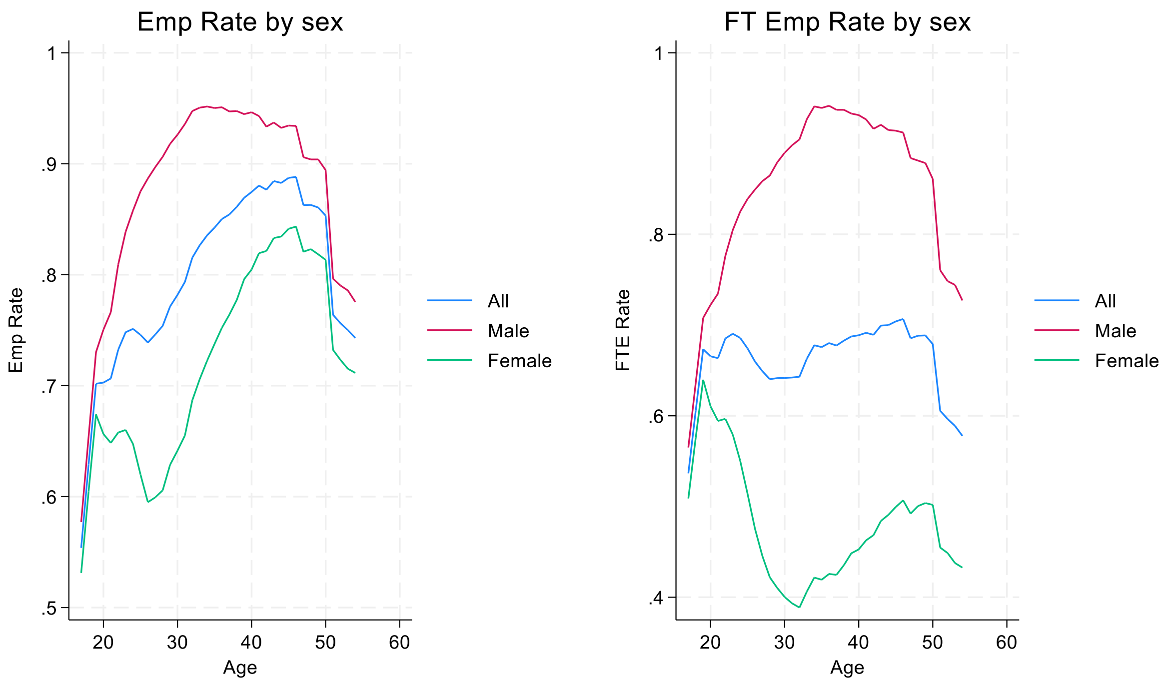
Table 4: Log Hourly Earnings at Survey Sweeps					
	23	**33**	**42**	**50**	**55**
Panel A: Men					
Standardized PGS	0.011	0.089	0.130	0.110	0.128
	(1.62)	(8.27)*	(9.81)*	(8.36)*	(9.03)*
Adj R-sq	0.015	0.052	0.053	0.056	0.77
Panel B: Women					
Standardized PGS	0.065	0.137	0.121	0.119	0.098
	(9.48)*	(12.70)*	(9.63)*	(10.90)*	(8.20)*
Adj R-sq	0.062	0.088	0.054	0.054	0.058
Panel C: Pooled					
Female	-0.165	-0.347	-0.411	0.352	-0.311
	(17.09)*	(22.74)*	(21.90)*	(21.19)*	(16.88)*
Standardized PGS	0.011	0.088	0.132	0.110	0.128
	(1.65)+	(8.23)*	(9.95)*	(8.38)*	(9.02)*
Female*Standardized PGS	0.054	0.050	-0.010	0.009	-0.030
	(5.68)*	(3.31)*	(0.54)	(0.53)	(1.59)
Adj R-sq	0.095	0.181	0.150	0.158	0.140
Unweighted N, Men	1,941	1,932	2,007	1,681	1,418
Unweighted N, Women	1,691	1,588	1,938	1,861	1,547
Unweighted N, Pooled	3,632	3,520	3,945	3,542	2,965

Notes: (1) T-stats in parentheses (2) Significance: + $p<0.10$ * $p<0.05$ (3) All models contain 20 principal components of the PGS and are weighted to account for attrition.

Table 5: Log Hourly Earnings at Survey Sweeps Including Those with Imputed Earnings					
	23	**33**	**42**	**50**	**55**
Panel A: Men					
Standardized PGS	0.008	0.066	0.097	0.085	0.075
	(1.45)	(7.49)*	(8.97)*	(8.11)*	(6.54)*
Adj R-sq	0.011	0.039	0.046	0.037	0.034
Panel B: Women					
Standardized PGS	0.045	0.083	0.076	0.096	0.062
	(7.91)*	(9.60)*	(7.46)*	(10.25)*	(6.51)*
Adj R-sq	0.028	0.045	0.035	0.050	0.027
Panel C: Pooled					
Female	-0.196	-0.350	-0.392	-0.364	-0.327
	(23.94)*	(27.98)*	(25.66)*	(26.66)*	(22.10)*
Standardized PGS	0.009	0.065	0.096	0.084	0.076
	(1.62)	(7.38)*	(8.92)*	(8.07)*	(6.55)*
Female*Standardized PGS	0.038	0.018	-0.019	0.013	-0.012
	(4.74)*	(1.43)	(1.29)	(0.93)	(0.83)
Adj R-sq	0.141	0.168	0.133	0.148	0.113
Unweighted N, Men	2,641	2,707	2,974	2,642	2,474
Unweighted N, Women	2,746	2,814	2,996	2,760	2,542
Unweighted N, Pooled	5,387	5,521	5,970	5,402	5,016

Notes: (1) T-stats in parentheses (2) Significance: + p<0.10 * p<0.05 (3) All models contain 20 principal components of the PGS, a dummy variable identifying those with imputed earnings, and are weighted to account for attrition.

Figure 1: Employment and Full-time Employment Over the Life Course by Sex



Appendix One: The Polygenic Score (PGS) for Educational Attainment

Genotyping for 13,738 samples (6,431 unique individuals in NCDS) was performed across seven different genotyping arrays. Quality control was completed using PLINK1.9, PLINK2.0, R v3.3.2 and RStudio v4.1.2. For each array individuals were excluded if they had more than 2% missing data; their genotype predicted sex using X chromosome homozygosity was discordant with their reported sex (excluding females with an F value > 0.2 and males with an F value < 0.8); they had excess heterozygosity (more than 3 standard deviations from the mean); or they were related to another individual in the sample (genome threshold 0.1875), removing samples with the most missing data.

Eagle2 was used to phase haplotypes, and Minimac4 with the HRC r1.1 reference panel used for imputation. Imputed genotypes were then filtered, excluding samples with more than 2% missing values, and SNPs with an R2 INFO score <0.8, >2 alleles, >3% missing values, Hardy-Weinberg equilibrium P<1e-6 or minor allele frequency <1%. Data were combined from five of the seven chips (Illumina 1.2M, Illumina Human 660-Quad, Infinium HumanHap 550K v1.1, Infinium HumanHap 550K v3 and Affymetrix v6) which had high and similar imputation quality (based on number of SNPs after quality control).

All samples except for five were covered by the other arrays and the combined dataset consisted of 6,420 individuals and 6,722,830 SNPs. Further quality control on the combined dataset excluded individuals who had > 2% missing values (9 individuals excluded) or were related to another individual in the sample (king-cutoff 0.0884) (16 excluded), whereby one individual from each related pair was excluded based on the KING greedy related algorithm. SNPs were excluded if they had high levels of missing data (>3%) (56,268 variants) or a Hardy-Weinberg equilibrium P<1e-6. Samples were further excluded if they were classified as non-European ancestry, determined by merging the combined cohort genotypes with data from 1000 genomes Phase 3, linkage disequilibrium pruning the overlapping single nucleotide polymorphisms (SNPs) such that no pair of SNPs within 50 bp had r2 > 0.20 and visually inspecting the first two genetic principal components along with the known ethnicities of the 1000 genomes sample to define European samples (83 excluded). The final quality controlled imputed set of genotypes contained 6,312 samples and 6,663,631 SNPs.

The PGS was derived from the largest GWAS of educational attainment to date (Okbay et al., 2022) using summary statistics from the clumped results of the additive GWAS meta-analysis of all discovery cohorts for approximately independent autosomal SNPs at $p<1e-5$. For all SNPs that reached $p<1e-5$ in the GWAS and were available in the NCDS, GWAS estimated SNP effect sizes were multiplied by the number of copies (0,1,2) that an individual had at each SNP, and then summed to give a total PGS. Selecting SNPs at SNPs at $p<1e-5$ reduces the likelihood that we include non-causally related SNPs in our analyses. We further derived a more restrictive PGS at the common GWAS significant threshold of $p<1e-8$ to use in analyses as PGS robustness checks.

The PGSs accounted for between 6 and 10 percent of the variance in the highest qualification achieved in our data, depending on which of the two PGSs is used and the age and sex of the cohort member.

Appendix Two: Methodology used to account for non-random selection into employment

If one wishes to extrapolate about the size of the gender wage gap estimated for employees to the population of men and women, one needs to adjust for non-random selection into employment which differs between men and women over the life-course. As noted by Bryson et al. (2020, Appendix A2) a variety of methods have been adopted to tackle this issue in the gender wage gap literature. The appropriateness of methods is data dependent. Here we deploy the same methodology as Bryson et al. (2020, Appendix A3) which they adapted from Neuberger et al. (2011). It entails imputing a wage for four types of individuals: those in employment without a wage observation; the self-employed; the unemployed; and the economically inactive. These imputed wages come from nearest neighbour wage 'donors' defined as those in the waged employment group at the same sweep from the same sex who are nearest in their propensity for waged employment to the non-waged individual. The nearest neighbours are identified through propensity score matching where the propensity to have a missing wage observation is estimated for each individual for each survey sweep.[7]

The probits for the (0,1) being without a wage at the time of the survey sweep are run separately for men and women, by sweep so that nearest neighbours who are 'donors' of their wage to the non-waged are drawn from the same sex. These probits are run four times per sweep for men and women separately. On each occasion the estimation sample includes those in employment with a wage (who score zero on the dependent variable) and one of the four groups mentioned above (those in employment without a wage observation; the self-employed; the unemployed; and the economically inactive) who score '1' on the dependent variable as the group with missing wage data.

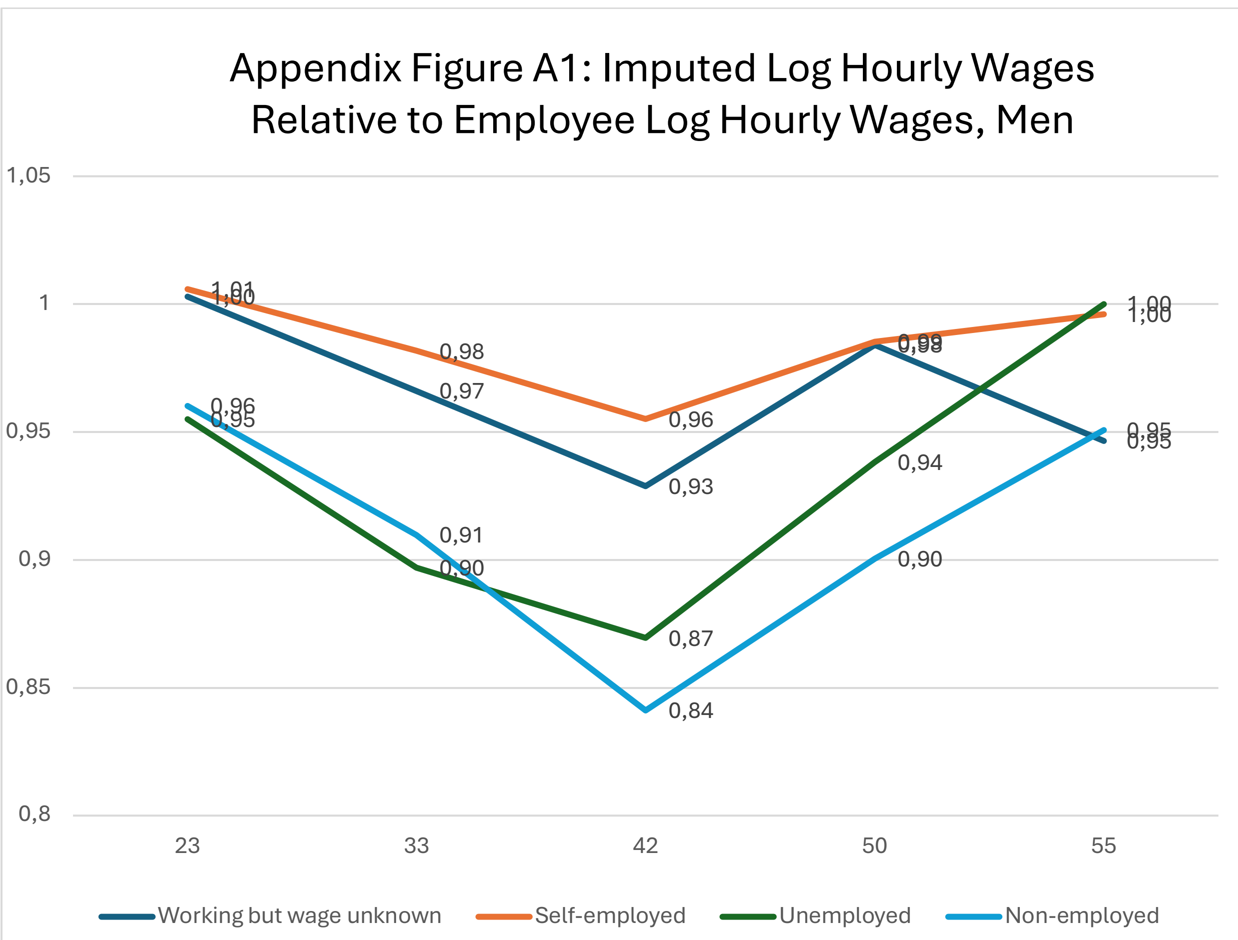
The covariates used to match those without wages and those with wages are listed in Appendix Table A1. (The dummy for part-time status is only used in matching in the case of the self-employed and those in employment without a wage since part-time status not relevant to the unemployed and economically inactive).

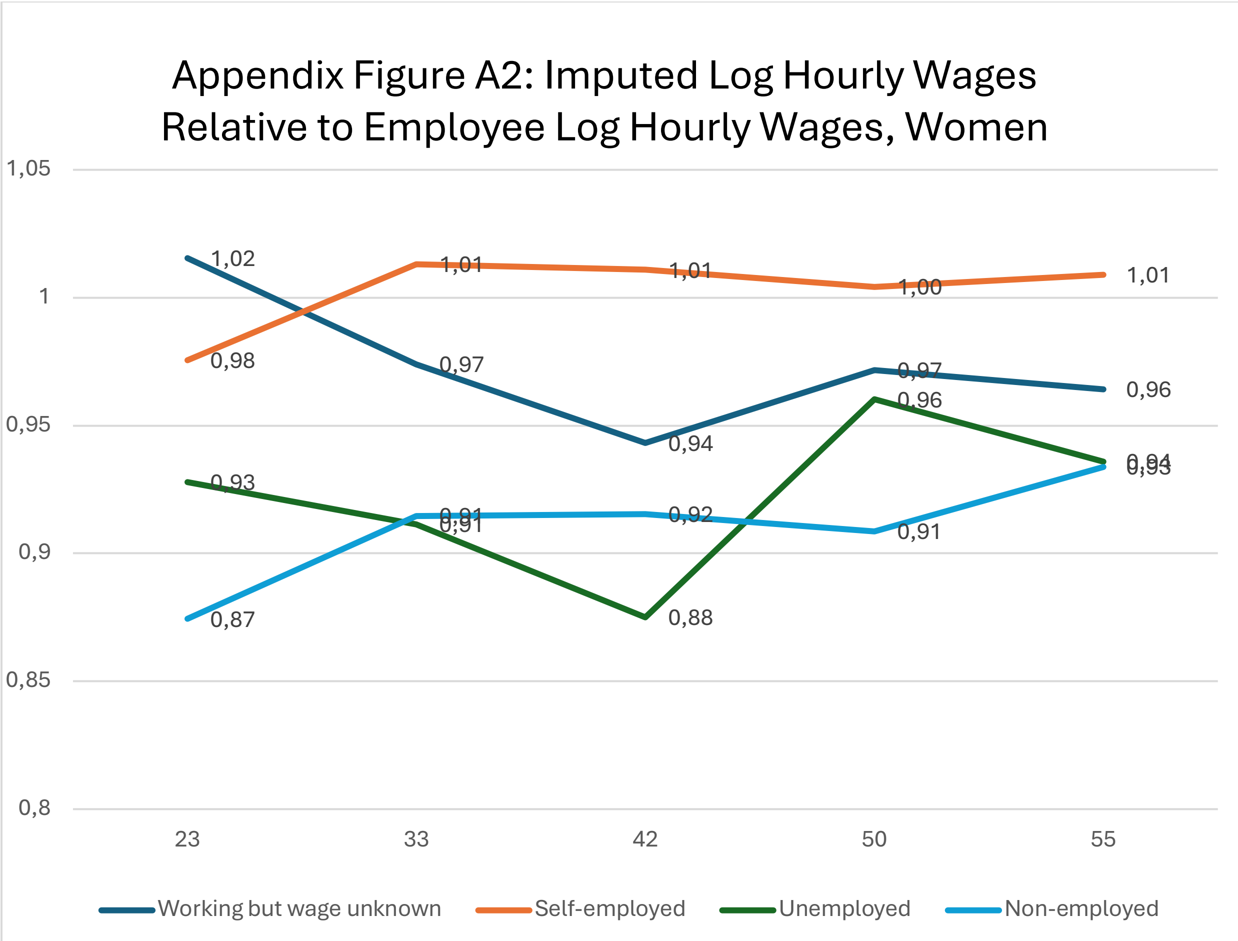
[7] We use the psmatch2 routine to implement single nearest neighbour matching with replacement without a caliper.

We enforce common support by dropping cases whose propensity for waged employment falls below the lowest probability for the waged employee sample at that sweep.

We also adjust for sample attrition by weighting the separate male and female wage equations by the inverse probability of responding to each sweep (see Appendix Three which describes how we account for attrition).

The imputed log hourly earnings of those who do not post an hourly wage are presented as a proportion of employees' log hourly wages at each sweep for men (Appendix Fig. A1) and women (Appendix Fig. A2) respectively, for the sample with a valid PGS. Except for the self-employed, whose imputed earnings are like those of employees, imputed earnings are substantially below those of employees posting an hourly wage in the case of both men and women.




Appendix Figure A2: Imputed Log Hourly Wages
Relative to Employee Log Hourly Wages, Women
1,05
1
0,95
0,9
0,85
0,8
23
33
42
50
55
1,02
0,97
0,94
0,97
0,96
0,98
1,01
1,01
1,00
1,01
0,93
0,91
0,88
0,96
0,94
0,87
0,91
0,92
0,91
0,93
Working but wage unknown
Self-employed
Unemployed
Non-employed

Appendix Table A1: Variables used in matching

Part-time worker	Dummy = 1 if self-defined part-time worker (<30 hours per week)
Work experience	
Full-time experience	Months in self defined full-time paid employment since age 16
Full-time experience squared	Months in self defined full-time paid employment since age 16 - squared
Part-time experience	Months in self defined part-time paid employment since age 16
Part-time experience squared	Months in self defined part-time paid employment since age 16 - squared
Highest qualification	
NVQ Level 1	Dummy = 1 if highest qualification is NVQ level 1 or equivalent
NVQ Level 2	Dummy = 1 if highest qualification is NVQ level 2 or equivalent
NVQ Level 3	Dummy = 1 if highest qualification is NVQ level 3 or equivalent
NVQ Level 4	Dummy = 1 if highest qualification is NVQ level 4 or equivalent
NVQ Level 5	Dummy = 1 if highest qualification is NVQ level 5 or equivalent
Missing	Dummy = 1 if information on highest qualification is missing
Test Scores	
Maths score	Standardized maths test score taken at age 10 (1970 cohort) or 11 (1958 cohort)
Missing maths score	Dummy = 1 if maths score missing
Reading score	Standardized reading test score taken at age 10 (1970 cohort) or 11 (1958 cohort)
Missing reading score	Dummy = 1 if reading score missing
Region	
London or SE	Dummy = 1 if living in London or the South East at time of survey
Presence of Children	
Children in household	Dummy = 1 if a child in the household by the time of the survey
Young child	Dummy = 1 if a child aged under 5 in the household at the time of the survey
More than 1 child	Dummy = 1 if more than one child in the household at the time of the survey
Social class of first job	
I	Dummy = 1 if first job in RG class I
II	Dummy = 1 if first job in RG class II
III NM	Dummy = 1 if first job in RG class III Non-Manual
III M	Dummy = 1 if first job in RG class III Manual
IV	Dummy = 1 if first job in RG class IV
V	Dummy = 1 if first job in RG class V
Missing	Dummy = 1 if information on occupation of first job is missing
Fathers social class	
I	Dummy = 1 if at birth father's job in RG class I
II	Dummy = 1 if at birth father's job in RG class II
III NM	Dummy = 1 if at birth father's job in RG class III Non-Manual
III M	Dummy = 1 if at birth father's job in RG class III Manual
IV	Dummy = 1 if at birth father's job in RG class IV
V	Dummy = 1 if at birth father's job in RG class V
Missing	Dummy = 1 if information at birth on father's job is missing
Age of parents	
Mother's age	Mother's age last birthday in years at birth sweep
Mother's age missing	Dummy = 1 if information missing
Father's age	Father's/ husband's age at birth sweep
Father's age missing	Dummy = 1 if information missing
Age mother left education	
Left before 16	Dummy = 1 if age left was less than 16
Left aged 16 or 17	Dummy = 1 if age left was 16 or 17
Left at 18 or more	Dummy = 1 if age left was 18 or more
Missing	Dummy = 1 if information missing
Age father left education	
Left before 16	Dummy = 1 if age left was less than 16
Left aged 16 or 17	Dummy = 1 if age left was 16 or 17
Left at 18 or more	Dummy = 1 if age left was 18 or more
Missing	Dummy = 1 if information missing
Number of siblings at age 16	
Only child	Dummy = 1 if had no siblings at age 16
One sibling	Dummy = 1 if had one sibling at age 16
Two or three siblings	Dummy = 1 if had two or three siblings at age 16
Four or more siblings	Dummy = 1 if had four or more sibling at age 16

Appendix Three: Methodology for adjusting for sample attrition

Appendix Table A2: Number of respondents and non-respondents by sweep and gender

	Respondents			**Non-respondents**		
	Men	Women	**Total**	**Men**	**Women**	**Total**
Age 23	5,972	5,999	11,971	2,199	1,866	4,065
Age 33	5,478	5,700	11,178	2,693	2,165	4,858
Age 42	5,569	5,739	11,308	2,602	2,126	4,728
Age 50	4,814	4,949	9,763	3,144	2,745	5,889
Age 55	4,356	4,623	8,979	3,443	2,958	6,401

Appendix Table A2 indicates there is substantial sample attrition across sweeps. Cohort members who had died or emigrated before the Biomedical Survey were not included in the target sample, so that the estimation sample was 16,036 at ages 23, 33, and 42. We also removed those who died or subsequently emigrated by ages 50 and 55, which is why the estimation samples dropped to 15,652 at age 50 and 15,380 at age 55. The response rate for eligible cohort members was 75% at age 23, dropping to 70% at age 33, only to rise a little to 71% at age 42, before falling to 62% at age 50 and 58% at age 55.

Adjustments for sample attrition involved estimating a probit model of the probability of responding to a survey sweep and taking the inverse of the predicted probability of response. There were separate models for each survey sweep by gender. For each sweep the response variable takes the value 1 when the outcome of the interview was productive for the given person; and 0 if the cohort member was available for interview but did not respond in the given sweep. Cohort members who died or emigrated were not included in the target sample for that sweep. When there was missing data for covariates, missing dummies were included. For continuous variables, the values of covariates were assigned the mean of known values for each sweep and gender.

For each model the values of weights which were below the 1st percentile and above 99th percentile, were replaced by values at the 1st and 99th percentile respectively. These probability weights were then applied to the employment and earnings estimates to give estimates of the gender employment and wage gaps that are adjusted for attrition.

Appendix Table A3 provides a description of the variables used in the probit attrition models. The models themselves are presented in Appendix Tables A4. The pseudo r-squared for the models ranged between 0.04 and 0.07.

Appendix Table A3: Variables used in models adjusting for sample attrition

Birthweight	Weight in ounces
Missing birthweight	Dummy = 1 if birthweight missing
South East	Dummy = 1 if region of birth is South East
Breastfeeding:	
None	Dummy = 1 if did not breastfeed
Up to 1 month	Dummy = 1 if breastfed for up to 1 month
More than 1 month	Dummy = 1 if breastfed for more than 1 month
Missing breastfeeding	Dummy = 1 if breastfed missing
Father Social Class 5	Dummy = 1 if father's social class at CM's birth was RG Class V
Missing Father's Social Class	Dummy = 1 if father's social class at CM's birth missing
Reading score age 7	Southgate reading test score
Missing reading score age 7	Dummy = 1 if CM's reading score age 7 missing
Bristol Social Adjustment Guide score	Score on BSAG at age 7
Missing Bristol Social Adjustment Guide	Dummy = 1 if BSAG at age 7 missing
Maths score age 11	Standardized maths test score taken at age 11
Missing maths score age 11	Dummy = 1 if maths score missing at age 11
Rutter score age 16	Rutter score at age 16
Rutter score missing age 16	Dummy = 1 if Rutter score missing at age 16

Appendix Table A4: Probit Regressions for Survey Response by Sweep and Sex										
	23 F	23 M	33 F	33 M	42 F	42 M	50 F	50 M	55 F	55 M
White	0.054	0.012	0.022	0.020	0.018	0.0022	-0.012	-0.0066	-0.0061	0.022
	(1.43)	(0.36)	(0.63)	(0.63)	(0.50)	(0.07)	(-0.37)	(-0.21)	(-0.19)	(0.70)
Breastfed (ref: no)										
Up to 1 m	-0.016	-0.0052	0.024	-0.017	-0.0034	-0.0034	-0.021	-0.049	0.037	-0.023
	(-0.34)	(-0.13)	(0.57)	(-0.45)	(-0.08)	(-0.09)	(-0.57)	(-1.41)	(1.02)	(-0.66)
> 1 month	-0.025	0.042	0.072+	0.078*	0.047	0.11*	0.056	0.097*	0.14*	0.14*
	(-0.52)	(0.98)	(1.65)	(2.00)	(1.06)	(2.67)	(1.43)	(2.62)	(3.58)	(3.89)
Don't know	-0.28*	-0.19*	-0.13*	-0.17*	-0.21*	-0.11*	-0.16*	-0.11*	-0.089+	-0.063
	(-4.92)	(-3.55)	(-2.51)	(-3.44)	(-3.81)	(-2.13)	(-3.29)	(-2.39)	(-1.84)	(-1.33)
Birthweight (kg)	-0.029	0.035	-0.042	0.070*	-0.0054	0.032	-0.033	-0.0087	-0.023	0.044
	(-0.75)	(1.01)	(-1.20)	(2.21)	(-0.15)	(0.99)	(-1.06)	(-0.29)	(-0.73)	(1.49)
Birth weight missing	-0.022	0.018	-0.019	-0.037	0.0093	-0.060	0.045	0.037	0.048	0.034
	(-0.48)	(0.42)	(-0.43)	(-0.97)	(0.21)	(-1.53)	(1.15)	(1.00)	(1.23)	(0.90)
Born in South East	-0.18*	-0.099*	-0.079*	-0.049	-0.028	-0.11*	0.038	-0.007	0.038	0.046
	(-4.86)	(-2.89)	(-2.25)	(-1.56)	(-0.80)	(-3.33)	(1.19)	(-0.02)	(1.20)	(1.54)
Father Social Class V	-0.10*	-0.081*	-0.10*	-0.18*	-0.047	-0.12*	-0.021	-0.13*	-0.077*	-0.13*
	(-2.72)	(-2.40)	(-3.04)	(-5.80)	(-1.36)	(-3.92)	(-0.66)	(-4.33)	(-2.52)	(-4.26)
DK Social Class	-0.100*	-0.12*	-0.087*	-0.11*	-0.054	-0.073+	0.016	-0.14*	-0.024	-0.13*
	(-2.14)	(-2.72)	(-2.02)	(-2.80)	(-1.23)	(-1.84)	(0.41)	(-3.76)	(-0.63)	(-3.45)
Southgate reading test score Age 7	0.12*	0.008	0.097*	0.079*	0.18*	0.044	0.18*	0.080*	0.19*	0.12*
	(2.79)	(0.00)	(2.34)	(2.05)	(4.45)	(1.13)	(4.76)	(2.17)	(5.02)	(3.34)
Reading missing	-0.28*	-0.085	-0.28*	0.014	-0.18+	0.13	-0.061	0.0038	-0.14	-0.018
	(-2.52)	(-0.75)	(-2.69)	(0.13)	(-1.72)	(1.20)	(-0.66)	(0.04)	(-1.52)	(-0.18)
BSAG age 7	-0.17*	-0.098*	-0.13*	-0.15*	-0.14*	-0.19*	-0.093*	-0.13*	-0.14*	-0.16*
	(-4.00)	(-2.40)	(-3.37)	(-3.94)	(-3.56)	(-4.95)	(-2.57)	(-3.64)	(-3.83)	(-4.42)
BSAG missing	0.11	-0.0092	0.070	-0.13	0.00089	-0.27*	-0.050	-0.096	0.034	-0.15
	(0.93)	(-0.08)	(0.67)	(-1.30)	(0.01)	(-2.60)	(-0.53)	(-0.96)	(0.36)	(-1.46)
Maths age 11, std	0.20*	0.23*	0.30*	0.20*	0.27*	0.31*	0.34*	0.29*	0.41*	0.40*
	(4.41)	(5.28)	(6.97)	(5.06)	(6.22)	(7.66)	(8.98)	(7.96)	(11.00)	(10.95)
Maths missing	-0.37*	-0.32*	-0.31*	-0.24*	-0.28*	-0.29*	-0.27*	-0.25*	-0.28*	-0.22*
	(-9.93)	(-9.19)	(-8.79)	(-7.61)	(-7.80)	(-8.91)	(-8.46)	(-8.06)	(-8.79)	(-7.00)
Rutter age 16	0.26*	0.23*	0.27*	0.080*	0.26*	0.047	0.17*	-0.0077	0.17*	-0.012
	(6.22)	(6.01)	(6.97)	(2.33)	(6.74)	(1.34)	(5.00)	(-0.23)	(4.84)	(-0.35)
Rutter missing	-0.035	-0.095*	-0.022	-0.079*	0.019	-0.11*	-0.030	-0.11*	-0.041	-0.14*
	(-0.87)	(-2.61)	(-0.60)	(-2.32)	(0.52)	(-3.26)	(-0.88)	(-3.41)	(-1.23)	(-4.46)

Obs	7865	8171	7865	8171	7865	8171	7694	7958	7581	7799
Log likelihood	-4015.1	-4551.5	-4359.6	-4954.5	-4336.5	-4864.6	-4765.1	-5111.8	-4752.8	-5016.9
chi2	588.1	414.3	536.8	449.9	506.5	495.8	495.6	455.6	635.2	670.7
Pseudo r2	0.0682	0.0435	0.0580	0.0434	0.0552	0.0485	0.0494	0.0427	0.0626	0.0627
Standardized beta coefficients; t statistics in parentheses + p<0.10 * p<0.05										