Does intelligence shield children from the effects of parental unemployment?

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Abstract

Current literature offers several potential channels through which parental unemployment can affect children. In this paper, I provide new evidence based on variation across intelligence that identifies loss of human capital investment as the driving mechanism. I find that higher intelligence mitigates some of the impacts, but not all. Parental unemployment is more harmful to the education of children with higher intelligence. This forces them to start their careers at lower-paying jobs and continues to weigh down on their wages even later in life. Nevertheless, higher intelligence helps narrow the gap labour supply, job ranking and monthly earnings over time.

JEL classifications: I21, J24, J62

Keywords: parental unemployment, intelligence, education, earnings, human capital investments, employer learning

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1 Introduction

The topic of how parental job loss affects children has recently received increased attention. Unemployment can impose large and prolonged costs directly on workers losing the job as well as indirectly on their children. The existing literature typically finds that having an unemployed parent has a negative impact on a number of educational and labour-market outcomes of children. These effects are especially pronounced among children from disadvantaged backgrounds[1]. However, various papers propose different channels through which parental unemployment affects children. In this paper, I present new evidence on how intelligence of children changes the effect of parental unemployment.

Studying the heterogeneity across intelligence distribution can improve our understanding of channels through which parental unemployment acts on children. On the one hand, higher cognitive skills can act as protective factors against negative shocks (Masten et al. 1999). In particular, there is some evidence suggesting that higher intelligence may help individuals cope better with stress (Santarnecchi, Rossi, and Rossi 2015; Weaver and Schofield 2015). Therefore, if parental unemployment during teenage years is operating through stress, then intelligence can be expected to act as a shield. On the other hand, the skill formation theory in Cunha and Heckman (2007) argues that returns to human capital investments positively depend on the existing level of skills. The implication is that teenagers with high intelligence are the ones to benefit the most from these investments. Therefore, if parental unemployment affects children mostly through losses in human capital investments, then higher intelligence can make children more vulnerable.

To estimate how the effect of parental unemployment on children differs across the intelligence distribution I use the UK Household Longitudinal Study (UKHLS) dataset. The UKHLS is the largest panel survey in the UK covering a wide range of topics. In particular, it includes information about cognitive test scores[2] of respondents and employment status of their parents at the time when respondents were 14 years old. This is also an important age in the context of the UK education system when children typically start in-depth preparations for school and university admission exams. This feature of the education system in the UK can contribute to large and potentially lasting effects of parental unemployment on trajectories of children, but also makes it easier to detect heterogeneities along intelligence distribution. The estimation strategy is based on a difference-in-differences framework. Causal interpretation

[1] Oreopoulos, Page, and Stevens (2008); Page, Stevens, and Lindo (2009)

[2] These tests broadly measure cognitive function of individuals focusing on various domains of cognitive ability. These are not achievement tests. I combine the test results into an intelligence score using principal component analysis.

of the estimation results relies on parallel trends assumption that requires selection bias to be constant across intelligence of children. I provide both empirical and simulation-based evidence in support of the assumption.

I present two key findings. First, higher intelligence makes children more vulnerable to the losses in education caused by parental unemployment. The probability of obtaining a tertiary degree falls as a result of parental unemployment by additional 3.6 percentage points for every one standard deviation increase in the intelligence score. This result is consistent with the dynamic complementarity theory of Cunha and Heckman (2007). In particular, the theory states that the productivity of human capital investments at later ages depends on the existing stock of skills. A relevant implication of this theory is that loss of human capital investments has larger consequences for adolescents with higher intelligence. Consistent with the prediction that only poor households adjust human capital investments in response to income shocks (Mulligan 1997), I show that the above result is a reflection of losses incurred by higher intelligence children of less educated parents.

My second finding is that, despite the negative effect on educational achievement, higher intelligence mitigates the effect of parental unemployment on labour-market outcomes later in life. The gap in employment probability and earnings caused by parental unemployment shrink by 4.8 percentage points and %, respectively, for every one standard deviation increase in intelligence. I also find that the positive effect on earnings gap is primarily due to higher labour supply. This can suggest that children at the top of the distribution continue to bear the cost of foregone education caused by parental unemployment even later in life.

The two sets of findings suggest that despite initially exacerbating the effect on educational attainment, high intelligence allows children to overcome these disadvantages over time. This result is consistent with the employer learning theory[3], which extends a standard signalling model by allowing employers to observe additional signals about worker productivity on the job. According to this theory, the role of educational signal in the wage-setting process decreases as workers accumulate experience. At the same time, the role of other characteristics, such as intelligence, rises. The theory presents two testable implications: i) the effect of parental unemployment on initial labour-market outcomes of children should not vary by intelligence score, and ii) the mitigating effect of intelligence should become stronger with experience. When individuals first enter the labour market, employers can only use their educational achievements to form a belief about worker productivity. Since children exposed to parental unemployment at the higher end of the intelligence distribution fail to obtain a university degree, they are initially unable to distinguish themselves from job candidates with

[3] Farber and Gibbons (1996); Arcidiacono, Bayer, and Hizmo (2010); Altonji and Pierret (2001)

lower skills. Therefore, the effect of parental unemployment on their first-job characteristics should not depend on the intelligence score. Indeed, I find that parental unemployment has same effect on the ranking of first jobs, regardless of intelligence. But as the individuals gain more experience, higher-intelligence workers can send additional signals about their productivity to improve their outcomes. Using a panel dimension of the UKHLS, I find that the age profiles are consistent with the mitigating effect of intelligence becoming stronger over time.

In the context of the discussion about channels through which parental unemployment affects children, the results in this paper suggest that losses in human capital investments are the main drivers. I provide additional heteorogeneity analysis that provides further support to this interpretation. The dynamic complementarity theory that was used to rationalise main results in terms of educational losses offers another testable prediction: human capital investments depend less on intelligence at earlier ages. Using the auxiliary dataset, the British Cohort Study 1970, I show that the interaction with intelligence is lower in magnitude when parental unemployment is measued at birth and at age 10. Moreover, the human capital losses are likely proportional to overall income losses. By exploiting the variation by parents' gender, I find that the main results mainly operate through father's unemployment. Since fathers were typically the primary earners in the family, their unemployment likely resulted in substantial drops in family income. Finally, I exploit the variation by children's gender to shed more light on potential role of stress channel. There is some evidence in the psychological literature that women and men experience and cope with stress differently. Therefore, if mental distress is driving at least some of the results, the interaction with intelligence could also differ by children's gender. However, I do not find support for this statement in the data.

This paper contributes to a growing literature on the intergenerational effects of parental unemployment. This literature has examined the effect of parental job loss on a variety of educational, labour-market and non-cognitive outcomes of children (for a detailed summary see Table **??**). Majority of the papers find large negative effects on educational outcomes[4], but small or zero effects on labour market outcomes of children[5]. Such variation can be related to institutional differences between countries in which the question has been studied (Lindemann and Gangl 2020). More importantly for the research question in the current paper, various papers propose different mechanisms that explain how parental job loss affects children. The most straightforward explanation is income loss. A common feature of

[4]Peter (2016); Brand and Thomas (2014); Pan and Ost (2014); Coelli (2011); Rege, Telle, and Votruba (2011); Stevens and Schaller (2011); Page, Stevens, and Lindo (2009); Bratberg, Nilsen, and Vaage (2008)

[5]Mörk, Sjögren, and Svaleryd (2019); Hilger (2016); Page, Stevens, and Lindo (2009); Bratberg, Nilsen, and Vaage (2008)

existing papers is that they typically find that losses are more severe among children from disadvantaged backgrounds[6]. Coelli (2011) provides some evidence that financial constraints may be modulating some of the effects of parental job loss by examining university tuition fees, household size and home ownership. Second channel put forward in the literature is mental distress. Rege, Telle, and Votruba (2011) do not find support for income channel and argue that the negative impact on children is consistent with mental distress and worsening parent-child interaction quality. Research by Akee et al. (2010) shows that positive effect of income gains on children's education is primarily driven by higher quality of parent-child time. This paper contributes to the discussion on mechanisms of parental unemployment effects by exploiting different interactions of these channels with intelligence of children. The results suggest that losses in human capital investment are driving the effects, especially in terms of educational outcomes. I also show that despite these losses, higher intelligence helps mitigate the losses in the labour market over time.

Additionally, my paper contributes to the literature exploring resilience to shocks along skill distribution. For example, Oreopoulos, von Wachter, and Heisz (2012) study the impact of graduating from college and entering the labour market during a recession. They find that the college graduates with higher predicted earnings, a proxy for higher skill, experience smaller losses on impact and recover more quickly thanks to higher job mobility. Similarly, Cygan-Rehm (2022) studies the effect of a German reform that shortened the duration of a school year on labour market outcomes of students. Although she did not directly examine heterogeneity across skill distribution, her estimates at different quintiles of earnings distribution suggest that children at the top of the distribution were unaffected and those at the bottom experienced significant reduction in lifetime earnings. To the extent earnings correlate with cognitive skills, these results could suggest that higher skills help dampen the negative shocks. In the biomedical literature, Santarnecchi, Rossi, and Rossi (2015) find that individuals with higher intelligence exhibit better brain resilience to insults. On the other hand, Gambi and Witte (2021) study the academic achievements of students in Belgium post-COVID19 and find that high-achieving students suffer the most from school closures during the pandemic. They argue that low-performing students were assisted by various programs aimed at mitigating their achievement deficits, while high-performing students were largely ignored by those policies. I contribute to this literature by examining directly how intelligence of children modulates their response to parental unemployment both in terms of educational attainment and subsequent labour-market outcomes.

[6] Pan and Ost (2014); Coelli (2011); Rege, Telle, and Votruba (2011); Page, Stevens, and Lindo (2009); Oreopoulos, Page, and Stevens (2008)

The remainder of the paper is outlined as follows. In the next section, I establish a conceptual framework of how different channels of parental unemployment effects can interact with intelligence of children. Section 3 describes the datasets and variables used in the analysis. Section 4 reviews the empirical strategy and assumptions necessary for the causal interpretation of the results. Section 5 presents the main results. In Section 6 I examine the robustness of findings to various specifications. Section 7 provides additional heterogeneity analysis in the context of the proposed mechanisms of parental unemployment effects. Finally, Section 8 concludes the paper.

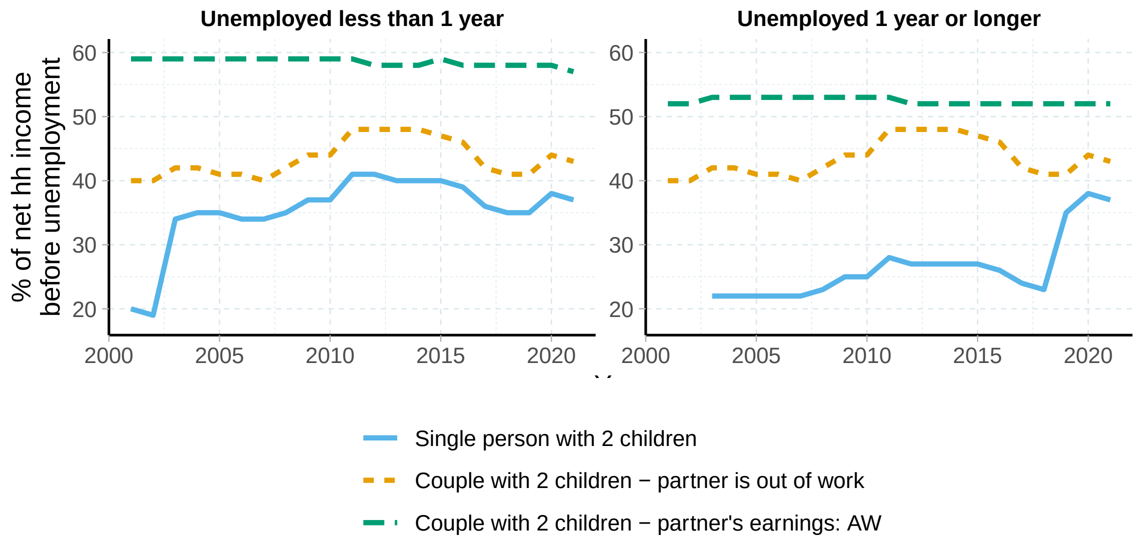
2 Parental unemployment and children's outcomes

The analysis in this paper uses parental unemployment measured at the time when children were 14 years old. The education system of the UK makes it also a relevant age at which to study the effect of parental unemployment. The negative impact of parental job loss on educational outcomes of children has been demonstrated in numerous studies (Oreopoulos, Page, and Stevens 2008; Page, Stevens, and Lindo 2009; Coelli 2011; Rege, Telle, and Votruba 2011; Brand and Thomas 2014; Pan and Ost 2014; Di Maio and Nisticò 2019). At the same time, the institutional environment can moderate the intensity of these effects (Lindemann and Gangl 2020). In Online Appendix A I describe the education system of the UK and argue that high selectivity of the university admission policies can contribute to large and potentially lasting effect of parental unemployment on children's outcomes. It also makes the heterogeneity by intelligence easier to detect.

The existing literature has highlighted several key channels through which parental unemployment can affect children. First is the drop in family income. Second, parental unemployment can increase stress and worsen socio-emotional skills of children. Third, unemployment can also affect beliefs of parents and children about virtues of education. Depending on the mechanism, intelligence of children can be either a protective or a risk factor, i.e., it can help dampen the negative effect of parental unemployment or exacerbate it.

Job loss is associated with large and persistent drop in household income: as much as 25% lower income five years after the job separation as reported by Jacobson, LaLonde, and Sullivan (1993). Similarly, Coelli (2011) finds that family income drops by as much as 17% four years following job loss by main income earner parent in Canada. According to the OECD (2023), the UK households with two children have on average about 40-50% lower net income compared to pre-displacement level if one parent loses a job. The share drops even further if both parents are unemployed or if it is a single-parent household (Figure 1).

Such large drops in family income can force parents to scale down investments into education of children[7]. How is loss of educational investments expected to interact with intelligence of children? For the answer, I turn to the skill formation theory of Cunha and Heckman (2007), in particular, the dynamic complementarity. The theory suggests that returns to the investments depend both on age of child and existing level of skills: children at the top of the skill distribution are the ones that benefit the most from investments in late childhood and adolescence. Therefore, if parental unemployment affects children through loss of income, children with high intelligence can be expected to lose the most.



Notes: The plots display net replacement rates of household income during unemployment in the UK as a share of previous in-work income by types of households and duration of unemployment. The data source is OECD (2023).

Figure 1: Net replacement rate of income during unemployment

Alternatively, parental unemployment can also have nonmonetary impact on families and children. Eliason and Storrie (2009) find evidence of higher stress following the job loss indicated by increased suicide rates and alcohol-related deaths. Charles and Stephens (2004) and Doiron and Mendolia (2012) also report that job loss can lead to higher probability of divorce among couples. The stressful environment can impact mental health of children as well as the quality of parent-child interactions (Brand and Thomas 2014; Rege, Telle, and Votruba 2011; Stevens and Schaller 2011; Akee et al. 2010). Furthermore, the ability of children to deal with stress resulting from parental unemployment can vary with their intelligence. For example, Weaver and Schofield (2015) find that children with higher cognitive ability are less affected by parental divorce. In the psychological literature, Masten et al. (1999) and Gale et al. (2009) find that intelligence acts as a protective factor against stress. Santarnecchi,

[7]See, for example, Chevalier et al. (2005) and Dearden, McGranahan, and Sianesi (2004) for the discussion of the importance of credit constraints for educational choices in the UK.

Rossi, and Rossi (2015) report that brain functions of individuals with higher intelligence are more resilient to shocks. If parental unemployment mainly operates through psychological distress, we can expect intelligence to dampen the negative effects.

Finally, unemployment can also alter the preferences for education of parents and children. Taylor and Rampino (2014) report that during recessions children may view school and university education as less important, mainly driven by children of parent with lower educational qualifications and with lower attitudes towards educational attainment of their children. There is also some evidence that parents' aspirations are more positive and accurate as children's intelligence increases (Murayama et al. 2016). This could suggest again that higher intelligence can protect children from lower education and career aspiration that may accompany parental unemployment.

3 Data

The main data source I am using is the UK Household Longitudinal Study (UKHLS)[8], also known as the Understanding Society, the largest household panel study of 40K individuals in the UK that started in 2009. The study covers a wide range of topics, including measures of cognitive ability and parental unemployment. The original study participants were sampled randomly from the UK population and their households were followed each year.

The analysis in this paper relies on the data from wave 3 covering 49,692 individuals, which in addition to the original sample includes participants continuing from a preceding British Household Panel Survey (BHPS). The dataset also contains cross-sectional weights that account for sampling and response probabilities in that wave. I restrict the analysis sample to individuals who (i) had non-zero sample weight (42,964); (ii) were born in UK (37,487); (iii) were born between 1950 and 1995 (26,895); (iv) attended and finished school (25,387); (v) complied with school-leaving-age law (23,335); (vi) lived in family at age 14 (22,930); (vii) had non-missing degree information (22,779). The condition that individuals were living in a family at age 14 is there to make sure that exposure to parental employment or unemployment can have an impact on individuals' outcomes. But it is important to note that this condition does not restrict the sample to individuals from dual-parent households. In fact, the sample includes 1,809 individuals from single-mother and 332 individuals from single-father households. More importantly, wave 3 of the UKHLS contains cognitive test results, which is essential for the analysis in this paper. Therefore, I also remove 1,571 individuals with missing intelligence score. Table 1 reports the descriptive statistics in the

[8] **ukhls<empty citation>**

Table 1: UKHLS descriptive statistics and missing intelligence score

	Sample incl. missing intelligence score			Sample excl. missing intelligence score		
Variable	mean	sd	N	mean	sd	N
Age	40.250	12.975	22,779	40.174	12.929	21,208
Female	0.513	0.500	22,779	0.510	0.500	21,208
British	0.937	0.242	22,432	0.939	0.239	20,892
Parents w/ degree	0.145	0.352	18,652	0.148	0.355	17,472
School-leaving age	16.601	1.057	22,640	16.622	1.061	21,088
Stay in school post-16	0.360	0.480	22,779	0.369	0.482	21,208
Degree	0.258	0.438	22,779	0.267	0.442	21,208
Work	0.726	0.446	22,779	0.735	0.441	21,208
Self-employed	0.090	0.287	22,779	0.091	0.288	21,208
IHS earn	2.594	1.649	22,740	2.638	1.635	21,170
Earnings $>$ 0	0.757	0.429	22,779	0.768	0.422	21,208
Earnings $>$ median	0.498	0.500	22,779	0.508	0.500	21,208

Notes: The table reports descriptive statistics in the working dataset before and after removing observations with missing intelligence score. Starting from the wave 3 of the UKHLS with 49,692 individuals, I restrict the sample to individuals who had non-zero sample weight, were born in UK, were born between 1950 and 1995, attended and finished school, complied with school-leaving-age law, lived in family at age 14, had non-missing degree information, had non-missing intelligence score. The left panel of the table reports the descriptive statistics for this sample, i.e., before removing individuals with missing cognitive test results. The right panel reports the descriptive statistics for the analysis sample of 21,208 individuals with non-missing cognitive test results.

analysis sample before and after removing individuals with missing intelligence score. The summary statistics show that the intelligence score is missing almost at random, in terms of observables.

I also present supporting evidence using the British Cohort Study 1970 (BCS70)[9], a longitudinal survey of individuals born in a week of 1970 in Great Britain. For a more detailed description of the dataset, working sample and variables see Online Appendix B.

3.1 Parental unemployment

Each respondent in the UKHLS was asked about employment status of their father and mother at the time when the respondent was 14 years old. The respondents reported whether their parents were working, unemployed, deceased or not living with them. For the main analysis, I only consider individuals whose parents were either working or unemployed and set the parental unemployment indicator to missing otherwise[10]. Out of 21,208 individuals in the analysis sample, 2,389 have missing employment status of father and 1,224 have missing employment status of mother. I use father's employment status as the primary source of

[9] **bcs70_s0<empty citation>**

[10] In Online Appendix F.1 I show that the results are robust to the inclusion of parental death and separation categories into the indicator of unemployment indicator.

information; unless the child is from a single-mother household, in which case I use mother's status. This is consistent with fathers being the primary earners (Figure G.1). The final parental unemployment indicator has 901 missing cases.

Since parental employment status is self-reported by the respondents, I compare it to various aggregate measures of unemployment in Online Appendix F.1. Somewhat surprisingly, the discrepancies are only observed among younger cohorts. In Section 6 I show that the results remain unchanged when the sample is restricted to cohorts in which parental unemployment matches closely the aggregate rates.

3.2 Intelligence score

In wave 3, the UKHLS administered cognitive ability questions among all respondents aged 16 and above. The five cognitive tests - word recall, serial 7 subtraction, number series, verbal fluency and numeric ability - were selected to be reliable, cover multiple domains of intelligence, and easy to administer (McFall 2013). I combine the counts of correct answers to each question into a single intelligence score using the principal component analysis (PCA). The first principal component, to which I refer to as "IQ", has eigenvalue of 2.526 and explains 42% of data variance. The first principal component attaches positive weights to all counts of correct answers, supporting the idea of using it as a variable summarising intelligence.

The cognitive tests were administered once during wave 3 of the UKHLS. Therefore, the test results contain not only signal about intelligence, but also age (Salthouse 2010) and cohort (Flynn 1984) effects (Figure E.1). To remove these effects, prior to running the PCA I standardized the test results within each birth cohort group, defined by five-year windows of year of birth, and gender. I also normalized the resulting intelligence score to zero mean and unit variance within each birth cohort group and gender. The goal of this paper is to compare otherwise similar children based on exposure to parental unemployment across intelligence distribution. Therefore, the above normalisation of intelligence score ensures that individuals are compared relative to their own peer group.

To further demonstrate that the first principal component is a good measure of intelligence, I show that it is positively correlated with all educational and labour market outcomes in Table 2. For example, a one standard deviation (sd) increase in intelligence score is associated with 14.5 percentage points (pp) higher degree attainment rate and 5.9 pp higher probability of working.

It is also worth noting that the analysis uses the intelligence measured at the time of the survey and interprets the results as if it were intelligence at the age of 14. In doing so, I am

Table 2: Average outcomes by intelligence score

	Dependent variables			
	Degree	Work	IHS earn	Current job rank
IQ	0.145	0.059	0.330	1.062
	(0.003)	(0.004)	(0.014)	(0.064)
Const.	0.267	0.735	2.630	-0.940
	(0.004)	(0.004)	(0.014)	(0.059)
Obs.	21,208	21,208	21,208	21,207

Notes: The table reports coefficients from weighted regressions of variables in columns on intelligence score. The IHS stands for inverse hyperbolic sine transformation; the corresponding coefficients could be converted to percentage change units (Bellemare and Wichman 2020). Standard errors clustered at the sampling unit are reported in parentheses.

implicitly assuming that relative position of an individual along the intelligence distribution remains unchanged over time. In Online Appendix E I discuss the existing literature studying the relative stability of intelligence, which typically support the statement. I also provide suggestive evidence based on repeated measurements of cognitive performance in the BCS70.

3.3 Educational outcomes

The dataset contains information about both continuous measures of education and qualifications. The continuous measures include age at which people left school and age at which they left further education. The latter variable is only valid for individuals who attended further education institutions. Therefore, I use the combination of two variables - age left school and age left further education - as a measure of total years of education.

From the information about highest qualifications, I construct an indicator variable that takes value of one if the highest qualification is a degree or higher. The base group in this indicator includes individuals with only school qualifications as well as those with post-school qualifications from non-degree programs. Therefore, I also use an indicator for staying in education past the compulsory age of 16.

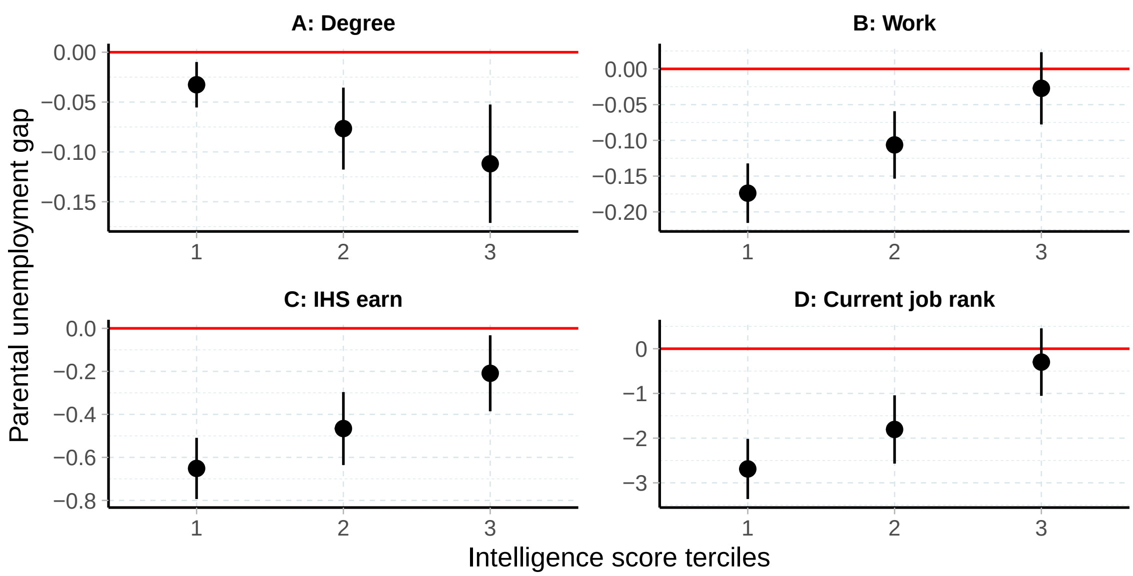
3.4 Labour market outcomes

In the main analysis, I use the outcomes reported during wave 3 of the UKHLS. I construct work indicator equal to one whenever respondents were employed in a paid job or self-employed and zero otherwise. I do not remove self-employed and unemployed individuals from the sample because this decision could be affected by parental unemployment. The survey also includes information about usual hours worked in a week among employed and self-employed respondents. I set hours worked to zero when it is missing[11].

I also use monthly labour earnings as well as hourly wages computed by dividing earnings with usual hours worked. I deflate both of them by the recommended consumer price index[12]. Since the earnings information can take zero or negative values among unemployed and self-employed workers, respectively, I cannot apply standard log transformation. The popular alternative in such cases is an inverse hyperbolic sine (IHS) transformation defined as $\text{arcsinh}(x) = \ln(x + \sqrt{x^2 + 1})$, which allows zero and negative values of transformed variable. However, this comes at the cost of interpretability: the regression coefficients can no longer be interpreted as elasticities. Following Bellemare and Wichman (2020), I convert the estimated coefficients to percentage change units.

Finally, I use job codes of current and first jobs ranked according to median earnings of similar workers at those jobs. In Online Appendix C I describe the ranking procedure in more detail.

3.5 Descriptive evidence



Notes: The figure plots parental unemployment discounts in terms of outcome variables in each panel by terciles of intelligence score. Parental unemployment discount is computed as the difference in sample mean among individuals with unemployed parents relative to those whose parents stayed employed.

Figure 2: Average outcomes by intelligence and parental employment

Before turning to the estimation strategy and results, I examine graphical evidence. Figure 2

[11] In the appendix section G I analyse the labour market outcomes in a two-step Heckman selection framework where hours worked and wages can only be observed when individual is working, which itself is affected by parental unemployment.

[12] CPI excluding rent, maintenance and water charges (Fisher et al. 2019)

plots the gap between outcomes of children with unemployed parents relative to those whose parents were employed across intelligence score terciles. First, the figure suggests that there is a discount associated with parental unemployment: the average outcomes are typically lower among children whose parents were unemployed. The magnitude of the discount is likely to be inflated due to selection bias, but the direction is consistent with the existing literature(Coelli 2011; Hilger 2016; Oreopoulos, Page, and Stevens 2008). Second, the discount varies with intelligence score of children. The gap in degree attainment is widening as intelligence score increases, but is shrinking in labour market outcomes. Notably, the gap in labour market outcomes is virtually non-existent at the top tercile of intelligence score.

The graphical evidence suggests that intelligence is likely to play a protective role against negative family shocks experienced during adolescence. But this is only visible in the longer term - after children enter the labour market and gain work experience. In the short term, children at the top of the distribution may be more vulnerable to parental unemployment. In the next section, I discuss the empirical strategy that allows me to study these relationships in a causal setting.

4 Empirical strategy

The goal of this paper is to estimate how intelligence changes the effect of parental unemployment on outcomes of children. The main specification of interest is

$$y_i = \beta_0 + \beta_1 UP_i + \beta_2 IQ_i + \beta_3 UP_i \times IQ_i + \beta_4 \mathbf{X}_i + \beta_5 \mathbf{P}_i + v_i \tag{1}$$

where y_i is outcome of individual i, UP_i is the indicator if a parent was unemployed when individual i was 14 years old; IQ_i is the intelligence score of individual i, $\mathbf{X}_i$ is the vector of predetermined characteristics of individual i, and $\mathbf{P}_i$ is the vector of predetermined parental characteristics of individual i. Here, β_1 captures the gap in outcomes of children with unemployed parents at average intelligence and β_2 captures linear effect of higher intelligence on outcomes among children whose parents stayed employed. The coefficient of interest β_3 estimates how the gap changes with intelligence score of children.

The indicator UP_i is likely to be endogenous to characteristics of the family and children, introducing selection bias to the estimators. Most of the papers studying the causal effect of parental unemployment on outcomes of children either exploit variation in children's age at the time of job loss (Pan and Ost 2014; Hilger 2016), use propensity score matching (Mörk, Sjögren, and Svaleryd 2019; Peter 2016), focus on plausibly exogenous job loss events

(Oreopoulos, Page, and Stevens 2008; Rege, Telle, and Votruba 2011; Stevens and Schaller 2011) or control for sufficiently long history prior to unemployment [Oreopoulos, Page, and Stevens (2008); Rege, Telle, and Votruba (2011);]. Unfortunately, the UKHLS provides limited information about parents of the respondents that is not sufficient for either of these strategies.

Note that the specification is similar to the difference-in-differences estimation. This allows causal interpretation of β_3 provided the parallel trends assumption applied to Equation (1) holds.

To put it more formally, denote potential outcome of an individual if exposed to parental unemployment shock as y^1. Similarly, the potential outcome, if her parents stayed employed as y^0. The realised outcome is then $y = y^0 \cdot (1 - UP) + y^1 \cdot UP$. For simplicity assume that IQ is a binary indicator for high intelligence. In Online Appendix D.1 I provide similar derivations with continuous measure of intelligence. All expectations that follow omit $\mathbf{X}$ and $\mathbf{P}$ from the conditioning set for simpler notation.

The parallel trends assumption in this setting can be expressed as

$$\begin{aligned}\mathbb{E}(y^0|UP = 1, IQ = 1) - &\mathbb{E}(y^0|UP = 0, IQ = 1) \\ &= \mathbb{E}(y^0|UP = 1, IQ = 0) - \mathbb{E}(y^0|UP = 0, IQ = 0)\end{aligned} \tag{2}$$

The left-hand side captures selection bias in the high-intelligence group, and the right-hand side - the bias in the low-intelligence group. Thus, the assumption requires the selection bias to be constant across intelligence distribution of children. To support the identifying assumption, I show in Online Appendix D.2 that the selection bias measured in terms of the observed pre-determined characteristics do not vary with intelligence of children. I also provide theoretical analysis of the parallel trends assumption in the context of intergenerational persistence of intelligence and its correlation with socio-economic status of parents in Online Appendix D.3. Due to data limitations[13], I use simulation study to show that the parallel trends assumption holds under constant persistence of intelligence[14].

Another assumption used in Equation (2) is that intelligence is not itself an outcome of parental unemployment. This assumption could be violated if education losses that result from parental unemployment also translate to lower intelligence. However, the intelligence measure I use in this paper is based on performance in general cognitive tasks and is not

[13] I observe cognitive measures of the UKHLS respondents, but not of their parents.

[14] Hanushek et al. (2021) show that there is positive correlation between skills of parents and skills of children and that the correlation is linear across the entire distribution.

based on achievement tests. While the existing literature has found achievement tests to be manipulable by events later in life, it is generally accepted that cognitive performance is set by age 10[15]. Nevertheless, in Online Appendix E.2 I discuss how the interpretation of β_3 changes if intelligence is an outcome of parental unemployment.

Given the parallel trends assumption, β_3 can indeed have a causal interpretation:

$$\beta_3 = \mathbb{E}(y^1 - y^0 | UP = 1, IQ = 1) - \mathbb{E}(y^1 - y^0 | UP = 1, IQ = 0) \tag{3}$$

It describes how the causal effect of parental unemployment varies with intelligence of children, evaluated among children whose parents were unemployed. Using the causality terminology and considering parental unemployment event as treatment, β_3 is the slope of the average treatment effect on the treated (ATT) with respect to intelligence.

5 Results

In this section, I present the results of estimation of Equation (1) in the UKHLS working sample. First, I start with the educational outcomes: ages when individuals left school and education, indicator for staying on at school past the compulsory age 16 (*post-16 school*) and having a degree (*degree*). The estimations control for the vector of pre-determined child characteristics $\mathbf{X}_i$ that include indicators for gender, year of birth, country of birth, race and immigrant status and for pre-determined parents' characteristics $\mathbf{P}_i$ that include indicators for highest educational qualifications and country of birth of each parent.

The results in Table 3 suggest that higher intelligence makes individuals more vulnerable to the losses in education attainment caused by parental unemployment. Parental unemployment reduces the probability of staying on at school and of having a tertiary degree by additional 3.5 pp and 3.6 pp, respectively, for every 1 sd increase in intelligence score. Similarly, for every 1 sd increase in intelligence score children leave school by 0.8 months earlier as a result of parental unemployment. The results may not appear large in comparison to the average outcomes in the analysis sample. But they constitute a large share of the correlation between the outcomes and intelligence score. For example, the estimated effect on degree attainment is equivalent to 25% reduction in its correlation with intelligence (Table 2), which can be attributed to parental unemployment.

[15] Heckman, Stixrud, and Urzua (2006); Cunha and Heckman (2007); Hopkins and Bracht (1975); Deary (2014). Notable exception is a recent paper by Carneiro et al. (2021), in which the authors show that redistributing family income from earlier to later ages can increases intelligence of children.

Table 3: Effect of parental unemployment on education of children by intelligence score

	Dependent variables			
	Age left school	Age left education	Post-16 school	Degree
Parent unemp	-0.167***	-0.239*	-0.081***	-0.039***
	(0.029)	(0.131)	(0.014)	(0.013)
IQ	0.301***	0.891***	0.138***	0.131***
	(0.008)	(0.038)	(0.004)	(0.004)
Parent unemp × IQ	-0.066††	-0.152	-0.035†††	-0.036†††
	(0.025)	(0.111)	(0.012)	(0.011)
Obs.	20,293	20,295	20,307	20,307
Outcome mean	16.62	19.32	0.37	0.27
Outcome sd	1.06	4.67	0.48	0.44

†q < 0.1; ††q < 0.05; †††q < 0.01 based on FDR adjusted p-values

*p < 0.1; **p < 0.05; ***p < 0.01 based on conventional p-values

Notes: The table reports coefficients from weighted regressions of dependent variables in columns on parental unemployment indicator and intelligence score. All regressions control for respondents' (gender, year of birth, country of birth, race, immigrant status) and parents' (highest educational qualifications and country of birth) characteristics. Standard errors clustered at the sampling unit are reported in parentheses. The p-values of the interaction coefficients are adjusted for multiple inference by controlling the false discovery rate (FDR) (Benjamini and Hochberg 1995).

These results show that higher intelligence exacerbates even further the losses in educational outcomes stemming from parental unemployment experienced at age 14. That is, instead of protecting children, higher intelligence makes them even more vulnerable to the negative shocks. Though surprising, the result is consistent with literature on human capital investments and skill formation. According to the theory of dynamic complementarity of skills (Cunha and Heckman 2007), human capital investments at later ages are more productive among children with already high level of skills. A particular implication of this theory is that loss of human capital investments has larger cost for children with higher levels of intelligence. The negative estimates in Table 3 are in line with this prediction. To fully support the implication of the dynamic complementarity theory, I need to show that children at the higher end of the ability distribution do lose human capital investments. Unfortunately, the data does not allow me to verify this statement directly. Instead, I rely on the theory of intergenerational transmission of earnings (Becker and Tomes 1986; Mulligan 1997), which predicts that only poor households reduce human capital investments as a result of income shock. In Table 4, I find that most of the additional losses associated with higher intelligence are borne by children with less educated parents[16], which are likely also children

[16]Parental educational qualifications are self-reported by children and are missing for about a fifth of the

Table 4: Effect of parental unemployment on educational outcomes of children by parental qualifications

	Post-16 school	Degree	Age left school	Age left education
Parent unemp × IQ	0.066	0.025	0.059	0.839†
	(0.042)	(0.048)	(0.077)	(0.403)
No school × Parent unemp × IQ	-0.146	-0.267††	-0.342	-1.154
	(0.106)	(0.106)	(0.236)	(1.514)
Some school × Parent unemp × IQ	-0.100†	-0.052	-0.117	-0.931†
	(0.045)	(0.050)	(0.083)	(0.416)
Qual missing × Parent unemp × IQ	-0.125††	-0.103†	-0.154	-1.579†††
	(0.049)	(0.052)	(0.098)	(0.513)
Obs.	20,307	20,307	20,293	20,295
Outcome mean	0.37	0.27	16.62	19.32
Outcome sd	0.48	0.44	1.06	4.67

†q < 0.1; ††q < 0.05; †††q < 0.01 based on FDR adjusted p-values

*p < 0.1; **p < 0.05; ***p < 0.01 based on conventional p-values

Notes: The table reports coefficients from weighted regressions of dependent variables in columns on parental unemployment indicator and intelligence score interacted with parents' highest educational qualification groups. The base group are parents with degrees. The regression controls for respondents' (gender, year of birth, country of birth, race, immigrant status) and parents' (highest educational qualifications and country of birth) characteristics. Standard errors clustered at the sampling unit are reported in parentheses. The p-values of the interaction coefficients are adjusted for multiple inference by controlling the false discovery rate (FDR) (Benjamini and Hochberg 1995).

from lower-income families.

Now, I turn to the labour-market outcomes of children: indicator for working (*work*), real monthly earnings (*IHS earnings*, which I also convert to *%Δ earnings* following Bellemare and Wichman (2020)), real hourly wages (*IHS hourly wage* and *%Δ hourly wage*), and usual hours worked per week (*hours*). The results for labour-market outcomes in Table 5 suggest that higher intelligence helps mitigate the cost of parental unemployment. Here, a 1 sd increase in intelligence score improves the effect of parental unemployment on the probability of employment by 4.8 pp and earnings - by 0.1 pp. The table also shows that the improvement in earnings is mostly due to higher labour supply[17]. These results suggest that intelligence does protect individuals from some of the consequences of negative family shocks in the longer term. Even though the cost on educational outcomes is highest at the upper end of

sample. I treat missingness as a separate category in the estimations. For interpretation of the results, I assume missingness to be a signal of low educational attainment.

[17]In Table G.1 I report the estimation results using a two-step Heckman selection correction. It explicitly accounts for the fact that earnings, hours worked and wages can only be observed if an individual is working, which could be viewed as a case of non-random sample. The results also show the mitigating effect of higher intelligence on earnings and hours worked.

Table 5: **Effect of parental unemployment on labour-market outcomes of children by intelligence score**

	Dependent variables					
	Work	IHS earnings	%Δ earnings	IHS hourly wage	%Δ hourly wage	Hours
Parent unemp	-0.061***	-0.276***	-0.279***	-0.017***	-0.116***	-2.752***
	(0.013)	(0.044)	(0.045)	(0.004)	(0.027)	(0.520)
IQ	0.052***	0.293***	0.296***	0.025***	0.161***	1.870***
	(0.004)	(0.014)	(0.014)	(0.001)	(0.009)	(0.154)
Parent unemp × IQ	0.048†††	0.126†††	0.130†††	-0.010††	-0.051†	1.552†††
	(0.013)	(0.040)	(0.040)	(0.004)	(0.026)	(0.466)
Obs.	20,307	20,307	20,307	15,643	15,643	20,307
Outcome mean	0.74	2.63	2.63	0.16	0.16	25.52
Outcome sd	0.44	1.65	1.65	0.15	0.15	17.68

†q < 0.1; ††q < 0.05; †††q < 0.01 based on FDR adjusted p-values

*p < 0.1; **p < 0.05; ***p < 0.01 based on conventional p-values

Notes: The table reports coefficients from weighted regressions of dependent variables in columns on parental unemployment indicator and intelligence score. All regressions control for respondents' (gender, year of birth, country of birth, race, immigrant status) and parents' (highest educational qualifications and country of birth) characteristics. The IHS stands for the inverse hyperbolic sine transformation; the corresponding coefficients are converted to percentage change units in the next column (Bellemare and Wichman 2020). Standard errors clustered at the sampling unit are reported in parentheses. The p-values of the interaction coefficients are adjusted for multiple inference by controlling the false discovery rate (FDR) (Benjamini and Hochberg 1995).

the intelligence distribution, these individuals are able to overcome the disadvantages later in the labour market.

The result is consistent with the employer learning theory, which extends a traditional signalling model by allowing employers to learn about worker productivity over time. In a traditional signalling model, workers can signal or reveal their ability only via education at the time of entering the labour market. Wages are set according to the observed educational qualifications and do not change afterwards. Several papers have extended the traditional model by allowing employers to learn about worker productivity from their work performance (Farber and Gibbons 1996; Altonji and Pierret 2001; Arcidiacono, Bayer, and Hizmo 2010). When workers can send additional signals about their productivity after entering the labour market, the initial educational signal becomes less important in wage setting and the returns to ability start increasing as workers gain more experience. Therefore, this theory offers an explanation for the positive results in terms of labour market outcomes: despite not being able to obtain a degree, high-ability workers can demonstrate their skills on the job and, thereby, mitigate the initial disadvantage.

The employer learning theory offers two testable implications. First, the effect of parental unemployment on early career outcomes should be flat with respect to intelligence score. Since high-intelligence children with unemployed parents fail to get a tertiary degree, initially they are not able to differentiate themselves from other job candidates. Second, the rate at which higher intelligence score improves the effect of parental unemployment on labour market outcomes should increase with work experience.

Table 6: Effect of parental unemployment on job ranking by intelligence score

	Dependent variables	
	IHS first job rank	IHS current job rank
Parent unemp	-0.039***	-0.234***
	(0.013)	(0.046)
IQ	0.029***	0.248***
	(0.004)	(0.013)
Parent unemp × IQ	0.005	0.159†††
	(0.012)	(0.043)
Obs.	16,400	20,307
Outcome mean	2.84	2.72
Outcome sd	0.50	1.54

†q < 0.1; ††q < 0.05; †††q < 0.01 based on FDR adjusted p-values

*p < 0.1; **p < 0.05; ***p < 0.01 based on conventional p-values

Notes: The table reports coefficients from weighted regressions of occupation rankings on parental unemployment indicator and intelligence score. Both current and first occupations were aggregated to major occupational groups (one-digit SOC) prior to ranking. Current occupations were ranked according to log of real weighted median earnings of individuals born in the same year in the UKHLS. First occupations were ranked according to log of real median earnings of 18-21 year olds in the year the respondent turned 20. The median occupational earnings of 18-21 year olds were computed using General Household Survey for years between 1972 and 1994 and downloaded from Office of National Statistics for years 1997 - 2019. All regressions control for respondents' (gender, year of birth, country of birth, race, immigrant status) and parents' (highest educational qualifications and country of birth) characteristics. Standard errors clustered at the sampling unit are reported in parentheses. The p-values of the interaction coefficients are adjusted for multiple inference by controlling the false discovery rate (FDR) (Benjamini and Hochberg 1995).

To test the first implication I estimate Equation (1) using the occupational ranking of children's first job and current job as dependent variables (Table 6). Indeed, the effect of parental unemployment on median earnings in the first job does not vary with intelligence score. The point estimates are close to zero in magnitude and are statistically insignificant. On the other hand, higher intelligence does improve parental unemployment effect on current job ranking. Thus, high-intelligence individuals that stopped their education paths earlier due to parental unemployment are initially pooled together with low-intelligence workers and begin their careers at lower-paying jobs. By the time of the survey, these high-intelligence workers manage to switch to better-paying jobs.

In order to test the second implication, I construct a panel dataset of earnings, hours worked and wages by merging the relevant variables from other waves of the UKHLS for the individuals in the analysis sample. Using this dataset I estimate the age profiles fully interacted with parental unemployment indicator and intelligence score of individuals. In particular, I estimate the following panel equation using the fixed-effect estimator

$$y_{it} = \gamma_0 + \gamma_{1a} + \gamma_{2a} UP_i + \gamma_{3a} IQ_i + \gamma_{4a} UP_i \times IQ_i + \gamma_{5a} z_i + \delta_t + c_i + \nu_{it} \tag{4}$$

where y_{it} is outcome of individual i at time t, z_i contains other individual characteristics constant over time such as gender, δ_t and c_i are time and individual fixed effects, respectively. The coefficients $\gamma_{1a}, \gamma_{2a}, \gamma_{3a}, \gamma_{4a}, \gamma_{5a}$ capture the age profiles of the outcome variables, where γ_{4a} is the set of age profiles of interest. It captures the differential impact of parental unemployment by intelligence of children over the life-cycle. It is well-known that the identification of the age profiles requires additional restriction on the coefficients (Deaton 1997). Borrowing the idea from Lagakos et al. (2018), I use the following restrictions that follows from economic theory: age profiles of a) wages are flat towards the end of the working life (between ages 45 and 55); b) hours worked are flat in the middle of the working life (between ages 35 and 55). These assumptions imply that earnings profile is also flat between ages 45 and 55. Thus, the age profiles are estimated relative to the base level at the restricted ages.

To formulate the null hypothesis, note that the second prediction from the employer-learning theory can be rewritten as

$$\frac{\partial \Delta \mathbb{E}(y^1 - y^0 | a)}{\partial a} \geq 0$$

where a is age and

$$\Delta \mathbb{E}(y^1 - y^0 | a) \equiv \mathbb{E}(y^1 - y^0 | UP = 1, IQ = 1, a) - \mathbb{E}(y^1 - y^0 | UP = 1, IQ = 0, a)$$

Let $a^\star$ denote the ages at which the profile is assumed to be flat (base ages). Since the flat portions of age profiles are towards the end of the working life, the assumption implies

$$\Delta \mathbb{E}(y^1 - y^0 | a < a^\star) - \Delta \mathbb{E}(y^1 - y^0 | a^\star) \leq 0$$

This condition can be translated to the null hypothesis $H_0 : \gamma_{4,a} \leq 0 \quad \forall a < a^\star$ and that γ_{4a} becomes less negative as age increases.

Table 7 reports the fixed-effect estimates of γ_{4a} in Equation (4). The results are consistent with

Table 7: Differential impact of parental unemployment by intelligence over the life cycle

	Dependent variable			
	Work	IHS earnings	IHS hourly wage	Hours
Ages 16-20	0.020	-0.469	-0.231**	-0.534
	(0.049)	(0.415)	(0.112)	(1.649)
Ages 21-25	0.017	-0.289	-0.151**	-0.551
	(0.036)	(0.334)	(0.066)	(1.176)
Ages 26-30	0.018	-0.404	-0.162**	-0.589
	(0.025)	(0.277)	(0.064)	(0.864)
Ages 31-35	0.009	-0.308	-0.085	-0.581
	(0.018)	(0.247)	(0.053)	(0.653)
Ages 36-40		-0.275	-0.068	
		(0.219)	(0.046)	
Ages 41-45		0.064	-0.052	
		(0.159)	(0.036)	
Ages 56-60	0.009	-0.004	0.002	0.198
	(0.021)	(0.178)	(0.050)	(0.819)
Ages 61-65	0.015	0.070	-0.055	0.812
	(0.036)	(0.271)	(0.070)	(1.280)
Obs.	175,072	175,124	134,279	175,124

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$ based on conventional p-values

Notes: The table reports the fixed-effects estimates of the differential impact of parental unemployment by intelligence of children over the life-cycle. Standard errors clustered at the individual level are reported in parentheses. Regressions are weighted by cross-sectional response weights from wave 3.

the null hypotheses stated above: the coefficients are negative and are gradually improving with age.

In summary, the results presented in this section suggest that intelligence can shield children from some of the effects of parental unemployment, but not all. The impact on educational attainment is worse at higher intelligence, which can be attributed to the dynamic complementarity of human capital investments. The affected individuals are then forced to start their careers at lower-paying jobs. Higher intelligence helps them to gradually move to more secure, better-paying jobs and mitigate the effect on earnings, consistent with the prediction of the employer learning theory. But they continue to bear the cost of foregone education later in life.

6 Robustness

I conduct a series of checks to show that the results are robust to alternative specifications and sample choices. In this section I provide a brief summary of the checks. Detailed descriptions and the results are presented in Online Appendix F.

First, I examine the robustness to parental unemployment measures in Online Appendix F.1. I begin by comparing the parental unemployment indicator in the data to various aggregate unemployment rates to assess potential bias of self-reported measure. The results remain largely the same once I restrict the sample to cohorts where unemployment measure is closely related to the aggregate rates. I also show that the results are robust to the inclusion of parental death and separation into the unemployment measure.

Another concern is that the parental unemployment indicator does not differentiate between unemployment and long-term non-employment. In Online Appendix F.2, I provide suggestive evidence based on neighbourhood characteristics at age 15 that the results are not driven by long-term characteristics of the families.

Next, I examine the robustness to different sample compositions that can be correlated with variations in exposure in Online Appendix F.3. The goal of these checks is to examine whether the results are driven by a single group of individuals. For example, individuals of different ethnicities may face different choice sets and institutional environments that can alter their response to parental unemployment. Similarly, households living in different countries of UK face different environments that can also change how they respond to parental unemployment. I find that the results remain largely unchanged. I also find that the estimates are slightly lower in magnitude when the sample is restricted to individuals born in Scotland, which could be related to a slightly less selective university admission system compared to England and Wales.

Finally, in Online Appendix F.4 I replicate the analysis in the BCS70. I use standardised intelligence score constructed from cognitive test results at age 10 and parental unemployment indicator measured at age 16. I construct the dependent variables to be as close as possible to their definitions in the UKHLS. The point estimates are less precise due to lower sample size. However, the replication results are largely in line with the main findings of the paper. Higher intelligence makes educational outcomes of children more vulnerable to losses caused by parental unemployment, but helps mitigate the impact on labour market outcomes. The results also appear to be increasing with age, providing additional support for the interpretation based on employer-learning theory.

7 Mechanisms of parental unemployment

The results in this paper suggest that intelligence is both a risk and a protective factor when it comes to how children respond to parental unemployment. At the beginning, it exacerbates the educational losses stemming from unemployment of parents. Later in the labour market, it allows them to find other channels to find more stable and prestigious jobs. The heterogeneous effects on educational outcomes directly relate to the discussion of mechanisms of parental unemployment effects on children in Section 2. In particular, the results suggest that loss in human capital investments are driving the effects. In this section I provide additional heterogeneity analysis that can support this interpretation.

First, I check the heterogeneity of these effects by age at which employment status of parents is measured in the BCS70[18]. The dynamic complementarity theory used to rationalise main findings in Section 5 also suggests that human capital investments at earlier ages are less dependent on intelligence of children. Therefore, if the primary channel is indeed loss of human capital investments, then there should be less heterogeneity by intelligence of children when unemployment is measured at earlier ages. The repeated surveys in the BCS70 allow a glimpse at parental employment statuses when children were 0, 10 and 16 years old. Table 8 report the corresponding estimation results from main specification across ages at which parental unemployment is measured. The results are consistent with the above prediction of the dynamic complementarity theory.

Furthermore, the losses in human capital investments should be proportional to income losses. Traditionally, fathers were primary earners in the family (Figures G.1 and G.2). Therefore, unemployment of fathers is more likely to result in a substantial reduction of family income. Therefore, the human capital investment channel is likely to operate via father's unemployment rather than mother's unemployment. In Table 9 I report estimation results where parental unemployment indicator is disaggregated by parent's gender. The results are in line with the prediction: father's unemployment status appears to be more relevant in explaining the heterogeneity by intelligence of children.

The discussion in Section 2 also highlighted another potential channel based on the findings in the existing literature: mental distress. For example, Rege, Telle, and Votruba (2011) argue that higher importance of father's job loss for children's outcomes is mostly the result of mental distress and drop in the quality of parent-child interactions. In this context, the results in Table 9, if taken alone, are also consistent with the mental distress intrepretation. To shed

[18] The UKHLS only contains information about a single snapshot of parental statuses at age 14 of the respondents.

Table 8: Degree attainment, IQ and parental unemployment across ages in the BCS70

	Dependent variable: Degree indicator		
	At birth	Age 10	Age 16
Parent unemp	0.004	-0.033*	-0.048*
	(0.025)	(0.019)	(0.025)
IQ	0.116***	0.126***	0.137***
	(0.005)	(0.006)	(0.008)
Parent unemp × IQ	-0.001	-0.069***	-0.085***
	(0.023)	(0.020)	(0.026)
Obs.	5,707	5,443	3,463

* p < 0.1, ** p < 0.05, *** p < 0.01

†q < 0.1; ††q < 0.05; †††q < 0.01 based on FDR adjusted p-values

*p < 0.1; **p < 0.05; ***p < 0.01 based on conventional p-values

Notes: The table reports estimation results from main specification with degree attainment as the dependent variable by ages at which parental unemployment is measured in the BCS70. Intelligence variable IQ is constructed from the first principal component based on cognitive test results at age 10. Parental unemployment is based on father's unemployment indicator if it is not missing; otherwise, mothers unemployment indicator is used. All regressions control for respondents' (gender, country of birth) and parents' (country of birth and age left education) characteristics. Regressions are weighted with inverse probability of response [@Mostafa2014] at corresponding ages. Standard errors are reported in parentheses.

Table 9: Effect of parental unemployment by parent gender and intelligence score

	Dependent variables					
	Degree	Work	%Δ earnings	%Δ hourly wage	IHS first job rank	IHS current job rank
IQ	0.133***	0.046***	0.279***	0.157***	0.033***	0.228***
	(0.004)	(0.005)	(0.016)	(0.010)	(0.004)	(0.016)
Father unemp	-0.037**	-0.055***	-0.246***	-0.123***	-0.028*	-0.215***
	(0.016)	(0.016)	(0.054)	(0.024)	(0.015)	(0.056)
Father unemp × IQ	-0.032	0.039	0.091	-0.081†	0.001	0.160†
	(0.014)	(0.017)	(0.051)	(0.029)	(0.014)	(0.054)
Mother unemp	0.010	-0.034***	-0.169***	-0.015	-0.021***	-0.122***
	(0.008)	(0.008)	(0.028)	(0.018)	(0.007)	(0.027)
Mother unemp × IQ	-0.001	0.016	0.032	0.006	-0.010	0.036
	(0.007)	(0.008)	(0.028)	(0.018)	(0.007)	(0.027)
Obs.	18,496	18,496	18,496	14,381	15,066	18,496

†q < 0.1; ††q < 0.05; †††q < 0.01 based on FDR adjusted p-values

*p < 0.1; **p < 0.05; ***p < 0.01 based on conventional p-values

Notes: The table reports coefficients from weighted regressions of dependent variables in columns on parental unemployment indicator and intelligence score interacted with parents' gender. All regressions control for respondents' (year of birth, country of birth, race, immigrant status) and parents' (highest educational qualifications and country of birth) characteristics. Standard errors clustered at the sampling unit are reported in parentheses. The p-values of the interaction coefficients are adjusted for multiple inference by controlling the false discovery rate (FDR) (Benjamini and Hochberg 1995).

more light on this channel, I explore the heterogeneity by gender of children[19]. In doing so, I

[19] Another way to interpret the variation by gender of children is through the lens of inter-household

assume that boys and girls experience and cope with stress differently[20]. Therefore, if mental distress is indeed one of the channels through which parental unemployment affects children, then the interaction with intelligence should be less negative for women, provided that higher cognitive skills are generally accepted to be a protective factor against stressful events (see discussion in Section 2). Table 10 reports estimation results from main specification separately by gender of respondents. I do not find support for the above statement in these results, at least in terms of educational outcomes. More positive interaction effects on earnings and employment of women may be related to gender differences in labour market participation patterns.

Table 10: Effect of parental unemployment by gender and intelligence score

	Dependent variables					
	Degree	Work	%Δ earnings	%Δ hourly wage	IHS first job rank	IHS current job rank
Parent unemp	-0.033*	-0.045**	-0.270***	-0.135***	-0.034*	-0.194***
	(0.020)	(0.019)	(0.067)	(0.031)	(0.020)	(0.067)
IQ	0.131***	0.052***	0.299***	0.172***	0.014**	0.235***
	(0.005)	(0.006)	(0.021)	(0.009)	(0.005)	(0.019)
Parent unemp × Female	-0.010	-0.028	-0.016	0.041	-0.009	-0.073
	(0.024)	(0.027)	(0.091)	(0.053)	(0.026)	(0.093)
IQ × Female	0.000	0.000	-0.006	-0.023	0.030***	0.026
	(0.006)	(0.008)	(0.026)	(0.018)	(0.007)	(0.025)
Parent unemp × IQ	-0.034	0.027	0.080	-0.066	0.001	0.091
	(0.017)	(0.020)	(0.067)	(0.034)	(0.018)	(0.068)
Parent unemp × IQ × Female	-0.004	0.037	0.093	0.032	0.004	0.120
	(0.021)	(0.026)	(0.086)	(0.051)	(0.024)	(0.088)
Obs.	20,307	20,307	20,307	15,643	16,400	20,307

†q < 0.1; ††q < 0.05; †††q < 0.01 based on FDR adjusted p-values

*p < 0.1; **p < 0.05; ***p < 0.01 based on conventional p-values

Notes: The table reports coefficients from weighted regressions of dependent variables in columns on parental unemployment indicator and intelligence score interacted with children's gender. All regressions control for respondents' (year of birth, country of birth, race, immigrant status) and parents' (highest educational qualifications and country of birth) characteristics. Standard errors clustered at the sampling unit are reported in parentheses. The p-values of the interaction coefficients are adjusted for multiple inference by controlling the false discovery rate (FDR) (Benjamini and Hochberg 1995).

redistribution of resources. Some existing literature documents that family resources may be split unequally between daughters and sons (Emerson and Souza 2007). However, this literature largely focuses on households in developing economies, and may not be directly applicable to the current setting.

[20]For example, girls are found to be more vulnerable to negative shocks in the form of receiving lower grades (Ost 2010; Owen 2010; Rask and Tiefenthaler 2008). That is, if girls receive lower grades in a subject, they are more likely to switch away from that subject; boys do not adjust their subject choices. In psychological literature, Matud (2004) report that women on average are more likely to report events from their lives as "more stressful and less controllable" (p.1401).

8 Conclusion

The topic of how parental job loss affects children has recently received increased attention. Many studies find that parental layoff has negative effect on various outcomes of children, especially pronounced among children from disadvantaged backgrounds. In this paper I provide new evidence on how intelligence of children changes the effect of parental unemployment. Using the UK survey data and difference-in-differences framework, I show that higher intelligence acts both as a risk and a protective factor. By exploiting the variation across intelligence, I also contribute to the ongoing discussion about mechanisms through which parental unemployment impacts children.

Initially, it exacerbates the cost on educational attainment of children. This finding is consistent with the dynamic complementarity theory (Cunha and Heckman 2007), which predicts that loss of human capital investments affects high-skill children more. Furthermore, I show that most of the damaging effect of high intelligence is concentrated among children with of educated parents - they are more likely to have experienced losses in human capital investments following parental unemployment.

Despite this, later in the labour market higher intelligence helps to narrow the gap in earnings and employment probabilities. These results are consistent with the employer learning model. I show that the impact of parental unemployment on occupation rank of the very first jobs does not vary with intelligence. That is, losses in education among high-intelligence children forces them to start their careers at lower paying job since they are unable to differentiate themselves from their peers. Using panel dimension of the dataset, I also show that mitigating effect of intelligence is gradually increasing with age. This is consistent with high-skill workers being able to send additional signals about their productivity to the employers.

These findings demonstrate that higher intelligence helps children to overcome some of the effects of parental unemployment experienced during adolescence, but not all. The results in this papper, especially in terms of educational attainment, suggest that income loss is the main channel through which parental unemployment affects children. I provide additional heterogeneity analysis in support of this interpretation. Using auxiliary dataset, I show that the role of intelligence as a risk factor for educational attainment increases in magnitude with age of children at which parental unemployment is measured. This is again consistent with the dynamic complementarity theory and supports the losses in human capital investments driving the results. I also show that the main findings operate through father's unemployment status, which can also support the income channel interpretation since father's unemployment likely translates to a more substantial drop in family income. Finally, I show that the interaction between parental unemployment and intelligence is same for men and women. Insofar as there are gender differences in stress levels and coping mechanisms, this could suggest that mental stress channel proposed in the literature is unlikely to play a significant role.

References

Akee, R. K., W. E. Copeland, G. Keeler, A. Angold, and E. J. Costello. 2010. "Parents' Incomes and Children's Outcomes: A Quasi-Experiment." *American Economic Journal: Applied Economics* 2 (1): 86–115.

Altonji, J. G., and C. R. Pierret. 2001. "Employer Learning and Statistical Discrimination." *The Quarterly Journal of Economics* 116 (1): 313–350.

Anger, S., and G. Heineck. 2010. "Do Smart Parents Raise Smart Children? The Intergenerational Transmission of Cognitive Abilities." *Journal of Population Economics* 23 (3): 1255–1282.

Arcidiacono, P., P. Bayer, and A. Hizmo. 2010. "Beyond Signaling and Human Capital: Education and the Revelation of Ability." *American Economic Journal: Applied Economics* 2 (4): 76–104.

Baird, J.-A., D. Caro, V. Elliott, Y. El Masri, J. Ingram, T. Isaacs, A. P. de Moira, et al. 2019. *Examination Reform: Impact of Linear and Modular Examinations at GCSE.* Report OUCEA/19/2. Oxford University Centre for Educational Assessment.

Becker, G. S., and N. Tomes. 1986. "Human Capital and the Rise and Fall of Families." *Journal of Labor Economics* 4 (3): S1–S39.

Bellemare, M. F., and C. J. Wichman. 2020. "Elasticities and the Inverse Hyperbolic Sine Transformation." *Oxford Bulletin of Economics and Statistics* 82 (1): 50–61.

Benjamini, Y., and Y. Hochberg. 1995. "Controlling the False Discovery Rate: A Practical and Powerful Approach to Multiple Testing." *Journal of the Royal Statistical Society,* Series B, 57 (1): 289–300.

Brand, J. E., and J. S. Thomas. 2014. "Job Displacement among Single Mothers: Effects on Children's Outcomes in Young Adulthood." *American Journal of Sociology* 119 (4): 955–1001.

Bratberg, E., Ø. A. Nilsen, and K. Vaage. 2008. "Job Losses and Child Outcomes." *Labour Economics,* European Association of Labour Economists 19th Annual Conference / Firms and Employees, 15 (4): 591–603.

Carneiro, P., I. L. García, K. G. Salvanes, and E. Tominey. 2021. "Intergenerational Mobility and the Timing of Parental Income." *Journal of Political Economy* 129 (3): 757–788.

Charles, K. K., and M. Stephens. 2004. "Job Displacement, Disability, and Divorce." *Journal of Labor Economics* 22 (2): 489–522.

Chevalier, A., C. Harmon, V. O'Sullivan, and I. Walker. 2005. *The Impact of Parental Income and Education on the Schooling of Their Children.* Working Paper WP05/05. Institute for Fiscal Studies.

Coelli, M. B. 2011. "Parental Job Loss and the Education Enrollment of Youth." *Labour Economics* 18 (1): 25–35.

Cunha, F., and J. Heckman. 2007. "The Technology of Skill Formation." *American Economic Review* 97 (2): 31–47.

Cygan-Rehm, K. 2022. *Lifetime Consequences of Lost Instructional Time in the Classroom: Evidence from Shortened School Years.* CESifo Working Paper 9892. Munich: CESifo.

Dearden, L., L. McGranahan, and B. Sianesi. 2004. *The Role of Credit Constraints in Educational Choices Evidence from NCDS and BCS70.* Discussion Paper 48. London: Centre for the Economics of Education.

Deary, I. J. 2014. "The Stability of Intelligence From Childhood to Old Age." *Current Directions in Psychological Science* 23 (4): 239–245.

Deary, I. J., S. R. Cox, and W. D. Hill. 2021. "Genetic Variation, Brain, and Intelligence Differences." *Molecular Psychiatry,* 1–19.

Deaton, A. 1997. *The Analysis of Household Surveys: A Microeconometric Approach to Development Policy.* Washington, DC: World Bank.

Di Maio, M., and R. Nisticò. 2019. "The Effect of Parental Job Loss on Child School Dropout: Evidence from the Occupied Palestinian Territories." *Journal of Development Economics* 141:102375.

Doiron, D., and S. Mendolia. 2012. "The Impact of Job Loss on Family Dissolution." *Journal of Population Economics* 25 (1): 367–398.

Eliason, M., and D. Storrie. 2009. "Does Job Loss Shorten Life?" *The Journal of Human Resources* 44 (2): 277–302.

Emerson, P. M., and A. P. Souza. 2007. "Child Labor, School Attendance, and Intrahousehold Gender Bias in Brazil." *The World Bank Economic Review* 21 (2): 301–316.

Farber, H. S., and R. Gibbons. 1996. "Learning and Wage Dynamics." *The Quarterly Journal of Economics* 111 (4): 1007–1047.

Fisher, P., L. Fumagalli, N. Buck, and S. Avram. 2019. "Understanding Society and Its Income Data."

Flynn, J. R. 1984. "The Mean IQ of Americans: Massive Gains 1932 to 1978." *Psychological Bulletin* (US) 95 (1): 29–51.

Gale, C. R., S. L. Hatch, G. D. Batty, and I. J. Deary. 2009. “Intelligence in Childhood and Risk of Psychological Distress in Adulthood: The 1958 National Child Development Survey and the 1970 British Cohort Study.” *Intelligence,* Intelligence, Health and Death: The Emerging Field of Cognitive Epidemiology, 37 (6): 592–599.

Gambi, L., and K. D. Witte. 2021. *The Resiliency of School Outcomes after the COVID-19 Pandemic. Standardised Test Scores and Inequality One Year after Long Term School Closures.* Discussion Paper DPS21.12. KU Leuven.

Hanushek, E., B. Jacobs, G. Schwerdt, R. van der Velden, S. Vermeulen, and S. Wiederhold. 2021. *The Intergenerational Transmission of Cognitive Skills: An Investigation of the Causal Impact of Families on Student Outcomes.* Working Paper w29450. Cambridge, MA: National Bureau of Economic Research.

Heckman, J., J. Stixrud, and S. Urzua. 2006. “The Effects of Cognitive and Noncognitive Abilities on Labor Market Outcomes and Social Behavior.” *Journal of Labor Economics* 24 (3): 411–482.

Higher Education in the Learning Society: Main Report. 1997. Report. London: The National Committee of Inquiry into Higher Education.

Hilger, N. G. 2016. “Parental Job Loss and Children’s Long-Term Outcomes: Evidence from 7 Million Fathers’ Layoffs.” *American Economic Journal: Applied Economics* 8 (3): 247–283.

Hopkins, K. D., and G. H. Bracht. 1975. “Ten-Year Stability of Verbal and Nonverbal IQ Scores:” *American Educational Research Journal* 12 (4): 469–477.

Jacobson, L. S., R. J. LaLonde, and D. G. Sullivan. 1993. “Earnings Losses of Displaced Workers.” *The American Economic Review* 83 (4): 685–709.

Lagakos, D., B. Moll, T. Porzio, N. Qian, and T. Schoellman. 2018. “Life Cycle Wage Growth across Countries.” *Journal of Political Economy* 126 (2): 797–849.

Lindahl, M., M. Palme, S. S. Massih, and A. Sjögren. 2015. “Long-Term Intergenerational Persistence of Human Capital: An Empirical Analysis of Four Generations.” *The Journal of Human Resources* 50 (1): 1–33.

Lindemann, K., and M. Gangl. 2020. “Parental Unemployment and the Transition into Tertiary Education: Can Institutions Moderate the Adverse Effects?” *Social Forces* 99 (2): 616–647.

Masten, A. S., J. J. Hubbard, S. D. Gest, A. Tellegen, N. Garmezy, and M. Ramirez. 1999. “Competence in the Context of Adversity: Pathways to Resilience and Maladaptation Fromchildhood to Late Adolescence.” *Development and Psychopathology* 11 (1): 143–169.

Matud, M. P. 2004. “Gender Differences in Stress and Coping Styles.” *Personality and Individual Differences* 37 (7): 1401–1415.

McFall, S. 2013. *Understanding Society: UK Household Longitudinal Study: Cognitive Ability Measures.* User Guide. Colchester, Essex: Institute for Social and Economic Research, University of Essex.

Mörk, E., A. Sjögren, and H. Svaleryd. 2019. *Consequences of Parental Job Loss on the Family Environment and on Human Capital Formation: Evidence from Plant Closures.* SSRN Scholarly Paper ID 3445825. Rochester, NY: Social Science Research Network.

Mostafa, T., and R. D. Wiggins. 2014. *Handling Attrition and Non-Response in the 1970 British Cohort Study.* CLS Working Paper 2014/2. Institute of Education, University of London.

Mulligan, C. B. 1997. *Parental Priorities and Economic Inequality.* Chicago and London: The University of Chicago Press.

Murayama, K., R. Pekrun, M. Suzuki, H. W. Marsh, and S. Lichtenfeld. 2016. "Don't Aim Too High for Your Kids: Parental Overaspiration Undermines Students' Learning in Mathematics." *Journal of Personality and Social Psychology* 111 (5): 766.

OECD. 2023. *Benefits and Wages: Net Replacement Rates in Unemployment.*

Oreopoulos, P., M. Page, and A. H. Stevens. 2008. "The Intergenerational Effects of Worker Displacement." *Journal of Labor Economics* 26 (3): 455–483.

Oreopoulos, P., T. M. von Wachter, and A. Heisz. 2012. "The Short- and Long-Term Career Effects of Graduating in a Recession." *American Economic Journal: Applied Economics* 4 (1): 1–29.

Ost, B. 2010. "The Role of Peers and Grades in Determining Major Persistence in the Sciences." *Economics of Education Review* 29 (6): 923–934.

Owen, A. L. 2010. "Grades, Gender, and Encouragement: A Regression Discontinuity Analysis." *The Journal of Economic Education* 41 (3): 217–234.

Page, M., A. H. Stevens, and J. Lindo. 2009. "Parental Income Shocks and Outcomes of Disadvantaged Youth in the United States." In *The Problems of Disadvantaged Youth: An Economic Perspective,* 213–235. University of Chicago Press.

Pan, W., and B. Ost. 2014. "The Impact of Parental Layoff on Higher Education Investment." *Economics of Education Review* 42:53–63.

Peter, F. 2016. "The Effect of Involuntary Maternal Job Loss on Children's Behaviour and Non-Cognitive Skills." *Labour Economics* 42:43–63.

Rask, K., and J. Tiefenthaler. 2008. "The Role of Grade Sensitivity in Explaining the Gender Imbalance in Undergraduate Economics." *Economics of Education Review* 27 (6): 676–687.

Rege, M., K. Telle, and M. Votruba. 2011. "Parental Job Loss and Children's School Performance." *The Review of Economic Studies* 78 (4): 1462–1489.

Salthouse, T. A. 2010. *Major Issues in Cognitive Aging.* Vol. 49. Oxford Psychology Series. New York: Oxford University Press.

Santarnecchi, E., S. Rossi, and A. Rossi. 2015. "The Smarter, the Stronger: Intelligence Level Correlates with Brain Resilience to Systematic Insults." *Cortex* 64:293–309.

Stevens, A. H., and J. Schaller. 2011. "Short-Run Effects of Parental Job Loss on Children's Academic Achievement." *Economics of Education Review* 20:289–299.

Taylor, M., and T. Rampino. 2014. "Educational Aspirations and Attitudes over the Business Cycle." *Economica* 81 (324): 649–673.

van Ham, M., L. Hedman, D. Manley, R. Coulter, and J. Östh. 2014. "Intergenerational Transmission of Neighbourhood Poverty: An Analysis of Neighbourhood Histories of Individuals." *Transactions of the Institute of British Geographers* 39 (3): 402–417.

Vandecasteele, L., and A. E. Fasang. 2021. "Neighbourhoods, Networks and Unemployment: The Role of Neighbourhood Disadvantage and Local Networks in Taking up Work." *Urban Studies* 58 (4): 696–714.

Weaver, J. M., and T. J. Schofield. 2015. "Mediation and Moderation of Divorce Effects on Children's Behavior Problems." *Journal of Family Psychology* (US) 29:39–48.

Willetts, D. 2017. *A University Education.* Oxford University Press.

Does intelligence shield children from the effects of parental unemployment?

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28 June 2023

Online Appendix

(Not meant to be part of the journal publication)

Appendix A Education system in the UK

In this paper I focus on the parental unemployment status when children were 14 years old. The timeline of key school exams as well as the university admission requirements make this age important: decisions made at this time can have lasting effects on lifetime outcomes.

The university education in the UK has been for a very long time elitist and dominated by Oxford and Cambridge. While university sector has significantly expanded in the 1960s and 1990s, the universities in the UK, and more importantly, individual departments within universities, continue to be highly selective towards their applicants (Willetts 2017). The selectivity of university admission means that the applicants must demonstrate good knowledge of the subject they want to study before starting the university program.

Typically, the way students can demonstrate such knowledge is via GCE A-level grades. The A-level exams are subject-specific and students usually sit three or four of them at the age of 18. In principle, students are free to choose any combination of subjects; in reality, the choices are shaped by the entry requirements of the programs they wish to apply to. Students usually study the subjects in-depth for two years before taking the exam[1]. The admission to the programs that prepare for A-level exams often require good grades in GCSE (General

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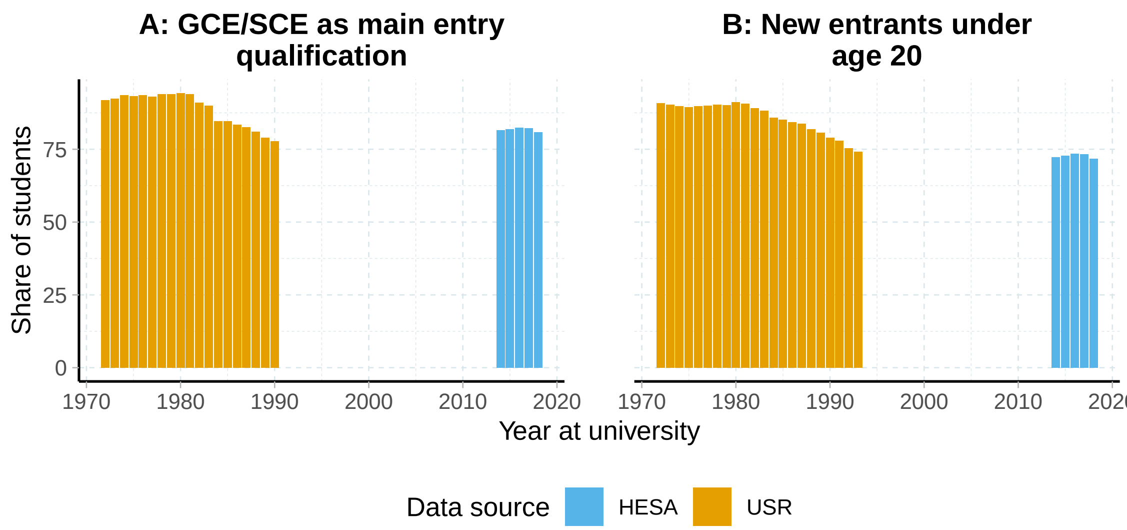
[1]The format has changed several times over the years. At first, each subject was designed as a two-year course with exams at the end of the course. Between late 1980s and 2000s, subjects gradually shifted towards modular approach, where a subject is split into modules and students take exams at the end of each module. Baird et al. (2019) find virtually no differences in grade outcomes between the two types of examinations, contrary to prior beliefs that modular examinations may be more favourable to some groups of students.

Certificate of Secondary Education)[2] exams taken at the end of compulsory school at age 16. Similar to A-level exams, GCSEs are also subject-based examinations for which students study in the last two-three years of secondary school. Students usually sit at least five GCSE exams in subjects of their choice. Universities may also take into account GCSE grades when making admission decisions.

Scotland has its own system of school-leaving qualifications. For most of my analysis sample the relevant qualification is Scottish Certificate of Education (SCE) that was in place during 1962-1999. The SCE had two grades: Ordinary (later Standard) and Higher, which are broadly equivalent to GCSE and AS-levels[3] in timing and importance. Ordinary Grades were typically taken at the age of 16, and Higher Grades - a year later. The main difference with GCSE and GCE is that Scottish qualifications aim at assessing broader knowledge; therefore, the exams were taken for a wider range of subjects. Admission to university was typically based on five SCE Higher exam results (*The Dearing Report* 1997). Furthermore, the undergraduate programs in Scottish universities typically include one year of foundation courses at the beginning (Willetts 2017). These facts suggest that the education system in Scotland is less selective than in the rest of the UK.



Notes: The plots display share of new entrants into university programs by entry qualifications and age using two sources: Undergraduate Records of the Universities' Statistical Record (USR) and Higher Education Statistics Agency (HESA). The USR contains detailed information on the population of undergraduate students in British universities between 1972 and 1993. HESA publishes aggregate tables, including student counts by personal characteristics and entry qualifications.

Figure A.1: Characteristics of new university entrants

The data confirms that majority of university students enter via main route: passing three or more A-level exams in the specified subjects. Figure A.1 demonstrates that about 80-90% of all first-time undergraduate students had GCE and/or SCE exam passes as the main entry

[2]Introduced in 1988, replacing the Certificate of Secondary Education (CSE) and more academically-targeted General Certificate of Education Ordinary Level (O level) qualifications, intended to unify the grading of the two. The reason for the unification was that CSE bunched together good and very good students, while O level - bad and very bad. Since they were two independent, separate qualifications, relatively better students at the tails of the distribution could not distinguish themselves.

[3]Approximately equivalent to half of A-level exam.

qualification and were under age 20. Therefore, the suggested timeline of first passing GCSE exams at 16 and GCE A-level exams at 18 is relevant for most of the children considering a university education.

To sum up, the selectivity of the university programs makes the grades in entry qualifications a very important factor. This in turn, translates to selectivity of the places that prepare for A level exams and places a high importance on the qualifications obtained at the end of compulsory school. In addition, GCSE grades may also enter directly into the admission decisions. Both qualifications require an in-depth study of the test subjects in the preceding two or three years. Such selectivity and hierarchy also makes alternative routes of entering university education more difficult. Therefore, if parental unemployment shock at the age of 14 alters educational choices of children, it can impact their lifetime outcomes.

Appendix B British Cohort Study 1970

The British Cohort Study 1970 (BCS70) is an ongoing longitudinal survey following over 17,000 children born in a week of 1970 in the Great Britain. Cohort members were surveyed both in childhood (ages 0[4], 5[5], 10[6], and 16[7]) and adulthood (every four years starting at age 26).

Starting from the initial sample of 17,196 children sampled at birth, I construct a panel dataset merging their responses from subsequent waves. This panel dataset is unbalanced due to sample attrition or unit non-response in some waves (Table B.1). To account for this, I construct inverse-probability weights similar to (Mostafa and Wiggins 2014). I estimate a logistic regression of the probability cohort member is observed in a given set of waves as a function of characteristics at birth: gender, birth order, lactation status, characteristics of mother (marital status, age at delivery, age left education) and characteristics of father (age left education and social class). The set of waves always includes surveys at ages 10 and 16, since these are the waves from which I extract intelligence score and parental unemployment, respectively.

Table B.1: BCS70 sample size across waves

	age 0	age 5	age 10	age 16	age 26	age 30	age 34	age 38	age 42
Obs.	17,196	12,748	13,775	10,728	8,332	10,442	8,961	8,232	9,116

Notes: The table reports number of initially sampled children at birth observed in subsequent waves of the BCS70. These may not correspond to the total observation count of the entire wave due to sample boosts.

Information collected at birth is of particular interest in this paper since it can be used to provide evidence supporting the main identifying assumption. The dataset includes both birth-related variables and socioeconomic characteristics of parents at birth. From the set of birth-related variables, I use birth weight, birth parity and lactation attempt. From parents' characteristics, I use age at delivery, marital status at delivery, age at first birth, country of birth of parents, age left education, and social class.

Another crucial feature of the BCS70 dataset in this paper is that cognitive tests were administered repeatedly at various ages of the BCS70 cohort members: at ages 5, 10, 16, 34 and 46. At each of these ages, I combine the test results into single intelligence score using the PCA. The first principal components have eigenvalues of 1.72 (30% of variation) at age 5, 2.28 (57%) at age 10, 2.60 (53%) at age 16, 1.51 (83%) at age 34[8] and 2.27 (38%) at age 46. The loadings of the first principal components assign positive weights to all test results. Given the evidence that most of the cognitive development takes place by age 10 (Hopkins and Bracht 1975; Cunha and Heckman 2007), I use the intelligence score at age 10

[4] **bcs70_s0<empty citation>**

[5] **bcs70_s1<empty citation>**

[6] **bcs70_s2<empty citation>**

[7] **bcs70_s3<empty citation>**

[8] The cognitive assessment at age 34 had only two parts measuring numeracy and literacy skills. Therefore, the PCA at age 34 is based on two variables, which also accounts for higher share of variance explained by the first principal component.

as the main indicator of intelligence of BCS70 cohort members. Out of 13,775 original cohort members observed at age 10, intelligence score is missing for 2,223 individuals. Table B.2 shows that, at least in terms of characteristics at birth, the subsamples with missing and non-missing intelligence scores are nearly identical.

Table B.2: BCS70 descriptive statistics and missing intelligence score

	Sample incl. missing intelligence score			Sample excl. missing intelligence score		
Variable	mean	sd	N	mean	sd	N
Female	0.481	0.500	13,775	0.482	0.500	11,552
Birthweight, g	3,314.270	526.474	13,763	3,320.110	528.747	11,542
Parity	1.234	1.404	13,758	1.225	1.379	11,543
Height of mother, cm	161.062	6.437	13,646	161.031	6.437	11,451
Mother married	0.977	0.151	13,761	0.977	0.150	11,540
Age of mother	26.175	5.440	13,757	26.143	5.411	11,537
Age of father	29.015	6.412	11,085	28.955	6.357	9,336
Age mother left edu	15.653	1.989	13,672	15.649	1.938	11,466
Age father left edu	16.021	3.674	13,185	15.991	3.491	11,077
Mother unemp at birth	0.946	0.226	9,862	0.946	0.225	8,281
Father unemp at birth	0.031	0.173	12,860	0.030	0.171	10,796
Parents unemp at age 16	0.087	0.282	6,366	0.085	0.279	5,418

Notes: The table reports descriptive statistics of the characteristics at birth of the original BCS70 cohort members observed at age 10. The left panel of the table reports the descriptive statistics for the entire sample, i.e., including individuals with missing intelligence score. The right panel reports the descriptive statistics for the subsample excluding individuals with missing intelligence score. The summary statistics are weighted by the inverse probability weight of being observed at age 10.

In addition, the survey at age 34 also includes cognitive assessments of children of the BCS70 cohort members. I also construct intelligence score of children by aggregating these test results using PCA. Since children were at different ages at the time of assessment, I perform PCA separately by each year of age and gender of children. I standardize the final score to have zero mean and unit variance within each age-gender cell.

Similar to parental unemployment variable in the UKHLS, I record parental unemployment status at age 16. To construct the indicator I mainly use father's employment status, but if unavailable, also consider mother's employment status. Out of 10,728 original cohort members observed at age 16, parental employment information is missing for 4,065 individuals. Table B.3 shows that individuals with non-missing parental employment status come from a relatively more affluent background. Among those who had non-missing parental employment status, 9.3% had an unemployed parent.

Table B.3: BCS70 descriptive statistics and missing parental unemployment

	Sample incl. missing parental unemployment			Sample excl. missing parental unemployment		
Variable	mean	sd	N	mean	sd	N
Female	0.480	0.500	10,728	0.514	0.500	6,663
Birthweight, g	3,316.710	533.375	10,719	3,335.168	534.680	6,658
Parity	1.229	1.383	10,716	1.105	1.269	6,657
Height of mother, cm	161.112	6.465	10,631	161.508	6.462	6,607
Mother married	0.977	0.151	10,716	0.981	0.136	6,655
Age of mother	26.218	5.463	10,718	26.419	5.348	6,659
Age of father	29.032	6.423	8,815	29.173	6.234	5,642
Age mother left edu	15.649	1.993	10,660	15.866	2.118	6,621
Age father left edu	15.990	3.291	10,306	16.219	3.689	6,431
Mother unemp at birth	0.945	0.227	7,704	0.948	0.222	4,784
Father unemp at birth	0.030	0.171	10,005	0.027	0.161	6,264
IQ at age 10	0.042	1.001	8,615	0.187	0.976	5,418

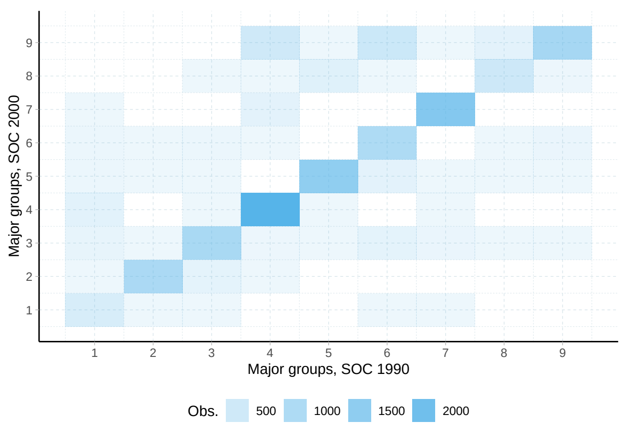
Notes: The table reports descriptive statistics of the characteristics at birth of the original BCS70 cohort members observed at age 16. The left panel of the table reports the descriptive statistics for the entire sample, i.e., including individuals with missing parental unemployment. The right panel reports the descriptive statistics for the subsample excluding individuals with parental unemployment. The summary statistics are weighted by the inverse probability weight of being observed at age 16.

Appendix C Occupation ranking

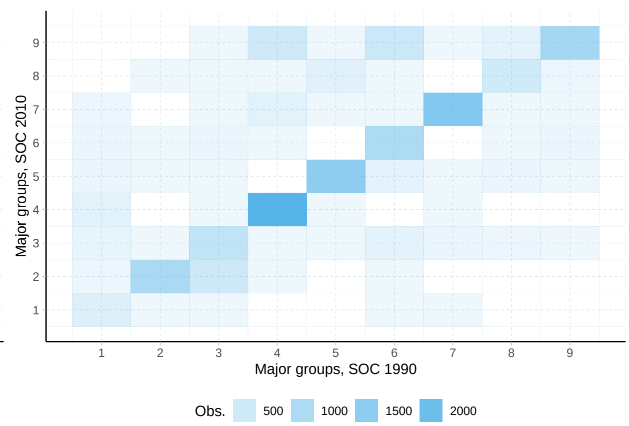
The survey also codes job titles of respondents current, last and first jobs using standard occupational classifications (SOC). The publicly available version of the dataset contains condensed[9] versions of SOC codes. I rank these occupations using median real earnings of the relevant population. For example, to rank how well-paid the respondent's first job was I would ideally use earnings of all labour market entrants in the same occupation in that year. To do so, I rely on the General Household Survey (GHS) for earnings information between 1972 and 1994 and aggregate tables from the Office for National Statistics (ONS) from 1997 onwards. Due to difficulty in translating occupational codes, even in condensed form, between different classification definitions, I aggregate SOC codes to one-digit major group level. By doing so, I am implicitly assuming that occupations rarely change major groups, which approximately holds between SOC revisions (Figure C.1). Then, for each respondent I merge major occupational group of her first job with median earnings of 18-21 year olds working in the same group in the year she turned 20 years of age. To rank current occupations, I use earnings information in the UKHLS of all sample members born in the same year. Here, I am not forced to collapse the occupation codes to one-digit level. But I do so, nonetheless, to ensure that the ranking of current job is comparable to the ranking of the first job. I deflate the median earnings in current job using the recommended consumer price index and the median earnings in first job - by retail price index[10].

[9] UK introduced the SOC in 1990 and revised it in 2000 and 2010 to keep the classification up to date. The SOC 1990 used three-digit codes but four-tier groups to classify occupations. Each occupation code (fourth tier) could be rounded down to the two-digit level describing the minor group (third tier) and one-digit level describing the major group (first tier). The second tier contained 22 sub-major groups, which could not be derived from occupational codes. Therefore, the SOC 2000 incorporated the sub-major groups into the occupational codes by moving to four-digit system. The publicly available version of the UKHLS contains condensed SOC codes, which means three-digit code in SOC 2000 and SOC 2010 and two-digit code in SOC 1990. The special-licence version of the UKHLS provides full codes.

[10] RPI series go further back in time than CPI.



(a) SOC 1990 vs SOC 2000



(b) SOC 1990 vs SOC 2010

Notes: The figure shows the frequency with which first jobs of individuals may end up in different major occupation groups depending on the different definitions of SOC. It uses the fact that the UKHLS codes job titles of each person using all three definitions of SOC. Then, I compute major occupational group under each definition and count observations in cells created by a pair-wise comparison of major groups. The observation counts are unweighted.

Figure C.1: Distribution of one-digit major groups of first jobs by SOC

Appendix D Parallel trends

Appendix D.1 Continuous case

The discussion of causal interpretation of β_3 in Section 4 considers the simple case with binary intelligence score. Here, I present the same discussion with continuous intelligence score.

Recall the main regression equation

$$y_i = \beta_0 + \beta_1 UP_i + \beta_2 IQ_i + \beta_3 UP_i \times IQ_i + \beta_4 \mathbf{X}_i + \beta_5 \mathbf{P}_i + v_i$$

For simpler notation, I omit $\mathbf{X}_i$ and $\mathbf{P}_i$ from the condition set in what follows. The parallel trends assumption in the continuous case requires that

$$\frac{\mathrm{Cov}(IQ, y^0|UP = 1)}{\mathrm{Var}(IQ|UP = 1)} = \frac{\mathrm{Cov}(IQ, y^0|UP = 0)}{\mathrm{Var}(IQ|UP = 0)}$$

With an additional assumption of linear conditional expectation function (CEF), I can rewrite this condition as follows:

$$\frac{\partial \mathbb{E}(y^0|UP = 1, IQ)}{\partial IQ} = \frac{\partial \mathbb{E}(y^0|UP = 0, IQ)}{\partial IQ}$$

The gap in pre-treatment outcomes of children with unemployed and working parents $\mathbb{E}(y^0|UP = 1, IQ) - \mathbb{E}(y^0|UP = 0, IQ)$ is the selection bias. Thus, similar to the binary case, the parallel trends assumption requires the selection bias to be flat in intelligence.

If the parallel trends assumption is satisfied, then the causal interpretation of β_3 can be written as

$$\beta_3 = \frac{\mathrm{Cov}(IQ, y^1 - y^0|UP = 1)}{\mathrm{Var}(IQ|UP = 1)}$$

Again, under linear CEF assumption, it can be presented as

$$\beta_3 = \frac{\partial \mathbb{E}(y^1 - y^0|UP = 1, IQ)}{\partial IQ}$$

That is, the coefficient β_3 describes how intelligence score of children changes the causal effect of parental unemployment among children whose parents were unemployed.

Appendix D.2 Test based on observed pre-determined characteristics

The causal interpretation of the estimation results relies on the parallel trends assumption in Equation (2), which essentially requires selection bias to be constant across intelligence distribution. The assumption is fundamentally untestable: I cannot observe outcomes of children with unemployed parents in the counterfactual world where their parents kept their jobs. However, I can provide supporting evidence based on observable characteristics that should not be affected by parental unemployment.

The idea is to use pre-determined characteristics as dependent variables in Equation (2). Even though these variables should not be affected by parental unemployment, selection bias may render $\beta_1 \neq 0$. But the crucial test is whether $\beta_3 = 0$. Since I am measuring effect on pre-determined characteristics that are not influenced by parental unemployment, the causal effect is zero for everyone, regardless of intelligence score. Thus, $\beta_3 = 0$ is a necessary condition of the parallel trends assumption. If the parallel trends assumption holds true, β_3 can be given causal connotation as in Equation (3).

Table D.1: Test of parallel trends assumption using predetermined characteristics in the UKHLS

	Regressors				
Dependent variable	Parent unemp	IQ	Parent unemp × IQ	Obs.	Mean outcome
Father's mother born UK	-0.007	-0.002	0.002	20,202	0.759
	(0.007)	(0.002)	(0.006)		
Father's father born UK	-0.011	0.002	0.006	20,202	0.750
	(0.007)	(0.002)	(0.006)		
Mother's mother born UK	-0.001	0.001	-0.003	20,202	0.773
	(0.006)	(0.002)	(0.006)		
Mother's father born UK	-0.009	0.005***	0.000	20,202	0.762
	(0.007)	(0.002)	(0.007)		
Has siblings	0.004	-0.000	-0.006	20,202	0.900
	(0.009)	(0.003)	(0.008)		
White british father	0.010	-0.000	-0.008	20,202	0.674
	(0.010)	(0.003)	(0.009)		
White british mother	0.015	-0.003	-0.005	20,202	0.680
	(0.010)	(0.003)	(0.010)		

†q < 0.1; ††q < 0.05; †††q < 0.01 based on FDR adjusted p-values

*p < 0.1; **p < 0.05; ***p < 0.01 based on conventional p-values

Notes: The table shows the results from regressions of predetermined variables in UKHLS shown in the first column on parental unemployment and intelligence score. All regressions control for respondents' (gender, year of birth, country of birth, race, immigrant status) and parents' (highest educational qualifications and country of birth) characteristics. Standard errors are reported in parentheses.

Table D.1 presents the regression results using a set of predetermined characteristics available in the UKHLS. Indeed, all the interaction coefficients are statistically insignificant and close

Table D.2: Test of parallel trends assumption using predetermined characteristics in the BCS70

Dependent variable	Regressors			Obs.	Mean outcome
	Parent unemp	IQ	Parent unemp × IQ		
At birth					
Parity	0.444***	-0.069***	0.024	5,063	1.50
	(0.094)	(0.022)	(0.085)		
Lactation attempted	-0.049**	0.031***	-0.026	5,063	0.32
	(0.024)	(0.008)	(0.024)		
Birthweight, g	-60.310*	57.119***	-10.030	5,059	3,284
	(35.011)	(9.956)	(30.745)		
Age of mother	0.575*	0.378***	0.380	5,063	26.18
	(0.325)	(0.082)	(0.307)		
Age of father	1.807***	0.440***	0.760	4,405	29.02
	(0.424)	(0.102)	(0.375)		
Height of mother, cm	-1.131***	0.346***	-0.033	5,029	161
	(0.369)	(0.109)	(0.326)		
Mother married	-0.015	-0.001	-0.005	5,063	0.96
	(0.016)	(0.004)	(0.013)		
Age of mother at first birth	-0.621***	0.485***	0.013	5,043	21.69
	(0.217)	(0.061)	(0.204)		
At age 5					
Composite score (PC1)	-0.123	0.267***	0.020	2,134	-0.05
	(0.088)	(0.037)	(0.072)		
Age at test, days	-0.771	-0.586	2.064	4,497	1,853
	(2.085)	(0.929)	(1.613)		
Reading score	-0.523	1.448***	-0.898	2,215	3.10
	(0.353)	(0.17)	(0.359)		
English picture vocab. score	-0.349***	0.375***	0.012	4,587	-0.34
	(0.091)	(0.025)	(0.084)		
Copying designs score	-0.052	0.393***	0.089	4,587	-0.10
	(0.062)	(0.017)	(0.056)		
Draw-a-man score	-0.109	0.288***	0.055	4,587	-0.17
	(0.077)	(0.02)	(0.078)		
Complete-a-profile score	-0.330	0.480***	0.016	4,431	6.85
	(0.258)	(0.072)	(0.251)		
At age 10					
Has normal vision	-0.033	0.005	0.000	4,800	0.86
	(0.023)	(0.006)	(0.023)		
At age 16					
Composite score (PC1)	-0.178*	0.579***	0.129	1,297	-0.07
	(0.1)	(0.026)	(0.103)		
Reading score	-2.791**	7.387***	2.646	1,377	53.58
	(1.368)	(0.351)	(1.459)		
Spelling score	-2.178	14.864***	2.697	5,063	74.11
	(4.753)	(1.365)	(4.205)		
Vocabulary score	-0.872	6.146***	-0.584	5,063	19.64
	(1.284)	(0.381)	(1.162)		
Math score	-0.185	6.102***	0.946	1,643	36.14
	(1.099)	(0.287)	(1.175)		
Complete-matrix score	-0.285*	0.575***	0.034	1,412	8.81
	(0.172)	(0.048)	(0.212)		

†q $<$ 0.1; ††q $<$ 0.05; †††q $<$ 0.01 based on FDR q-values
*p $<$ 0.1; **p $<$ 0.05; ***p $<$ 0.01 based on conventional p-values

Notes: The table shows the results from regressions of predetermined variables shown in the first column on parental unemployment at age 16 and intelligence score at age 10 in the BCS70. All regressions control for respondents' (gender, country of birth) and parents' (country of birth and age left education) characteristics. Estimations are weighted with inverse probability of response (Mostafa and Wiggins 2014). Standard errors are reported in parentheses.

to zero in magnitude. However, the set of predetermined variables available for the test in the UKHLS is rather limited: they are mostly related to ethnic background of parents and grandparents, which could already be captured by parents' country of birth and immigrant status indicators in $\mathbf{P}_i$ and $\mathbf{X}_i$. This explains nil main effects of parental unemployment and intelligence on the pre-determined characteristics seen in second and third columns of the table.

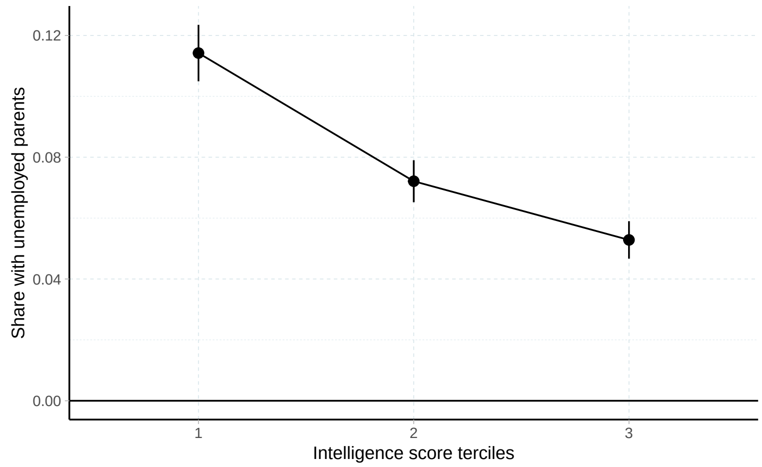
Therefore, I repeat the test using the BCS70 dataset. I use early waves that took place when children were just born, 5, 10, and 16 years old. The main regressors are intelligence scores measured at age 10 and parental unemployment indicators measured at age 16. The dataset offers a range of outcomes measured at birth, such as birth weight or lactation behaviour as well parent's characteristics at the time, which could conveniently serve as pre-determined characteristics not influenced by parental unemployment at age 16. The results are reported in Table D.2. Unlike the results in Table D.1, higher intelligence score is associated with better outcomes while parental unemployment - with worse outcomes on average. This suggests that testing whether interaction term is zero in this case is a more reasonable exercise. And, indeed, I find that the interaction coefficients are statistically insignificant, both before and after multiple-inference adjustment. Moreover, the magnitudes of the estimates are small relative to sample averages of the dependent variables. These results also support the identifying assumption of constant selection bias across intelligence scores; at least, based on observable pre-determined characteristics.

Appendix D.3 Intergenerational persistence of intelligence

In this section I examine what does the parallel trends assumption imply in terms of differential unemployment probabilities and intergenerational process on intelligence. As mentioned earlier, this assumption requires the selection bias to be constant across intelligence distribution. But it is not clear whether the assumption still holds knowing that parental unemployment probabilities vary with intelligence. Parents with high intelligence scores are less likely to be unemployed. They are also more likely to have high-intelligence children. It is not clear how these two facts affect the parallel trends assumption.

In economics, Becker and Tomes (1986), Anger and Heineck (2010), Lindahl et al. (2015) and Hanushek et al. (2021) show that intelligence scores are persistent across generations. In a survey of recent genetic research, Deary, Cox, and Hill (2021) report high values of heritability of intelligence, up to 70% among adults, a finding replicated across various settings. That is, high-intelligence parents are likely to raise high-intelligence children. Higher intelligence is also associated with higher probability of work (Table 2) or conversely lower probability of unemployment. Thus, the probability of a child having an unemployed parent is decreasing in intelligence score of children (Figure D.1).

Let's consider the intergenerational persistence of intelligence score more closely in the context of the parallel trends assumption. I start again with the binary intelligence case. Recall that in previous derivations variable IQ describes the intelligence score of the child. For clarity, denote now the intelligence score of the child as IQ_C and that of the parent as IQ_P. The persistence of intelligence score is then governed by two parameters $q_1 \equiv \Pr(IQ_C = 1|IQ_P = 1)$ and $q_0 \equiv \Pr(IQ_C = 1|IQ_P = 0)$. Then, intelligence has positive persistence if $q_1 > q_0$. I also allow



Notes: The figure plots the share of children with unemployed parents by terciles of children's intelligence score. The whiskers correspond to 95% confidence interval. The statistics are weighted by the cross-sectional response weight and clustered at the sampling unit.

Figure D.1: Parental unemployment by intelligence

persistence to vary with parent's intelligence, i.e., q_1 and q_0 do not necessarily add up to one.

Parental unemployment is a function of parent's intelligence: $u_1 \equiv \Pr(UP = 1|IQ_P = 1)$ and $u_0 \equiv \Pr(UP = 1|IQ_P = 0)$. The negative correlation between intelligence and unemployment implies that $u_1 < u_0$. Since I also assume that children's intelligence is not an outcome of parental unemployment, the two variables are conditionally independent of each other

$$\Pr(UP, IQ_C|IQ_P) = \Pr(UP|IQ_P)\Pr(IQ_C|IQ_P)$$

The parallel trends assumption in Equation (2) can be rewritten with parental intelligence as the pre-treatment outcome:

$$\begin{aligned} &\Pr(IQ_P = 1|UP = 1, IQ_C = 1) - \Pr(IQ_P = 1|UP = 1, IQ_C = 0) = \\ &= \Pr(IQ_P = 1|UP = 0, IQ_C = 1) - \Pr(IQ_P = 1|UP = 0, IQ_C = 0) \end{aligned} \tag{5}$$

After applying Bayes rule and rearranging the terms, Equation (5) can be rewritten as

$$\frac{q_1(1-q_1)}{q_0(1-q_0)} = \frac{u_0(1-u_0)}{u_1(1-u_1)}\left(\frac{1-p}{p}\right)^2 \tag{6}$$

where $p \equiv \Pr(IQ_P = 1)$ is the share of high-intelligence parents.

The ratio on the left-hand side of Equation (6) describes persistence of the intelligence score between generations.

$$\begin{cases} \frac{q_1(1-q_1)}{q_0(1-q_0)} = 1 \iff q_1 + q_0 = 1 & \text{(constant persistence)} \\ \frac{q_1(1-q_1)}{q_0(1-q_0)} > 1 \iff q_1 + q_0 < 1 & \text{(decreasing persistence)} \\ \frac{q_1(1-q_1)}{q_0(1-q_0)} < 1 \iff q_1 + q_0 > 1 & \text{(increasing persistence)} \end{cases}$$

I study the condition in Equation (6) numerically by evaluating it at all plausible combinations of parameters q_0, q_1, u_0, u_1 and p. I define the set of plausible combinations using the following constraints:

- Restrictions on intelligence process
  - p is a function of $\Pr(IQ_C = 1) = 0.5$, q_0 and q_1: $p = \frac{\Pr(IQ_C=1)-q_0}{q_1-q_0}$.
  - Parameter bounds: $0 < p < 1 \Rightarrow q_0 < \Pr(IQ_C = 1) < q_1$.
  - No perfect persistence: $q_0 > 0$ and $q_1 < 1$
- Restrictions on unemployment process
  - Unemployment rates are not deterministic: $u_0 < 1$ and $u_1 > 0$.
  - Unemployment probability decreases with intelligence: $u_0 > u_1$
  - Upper bound on observed unemployment rates:

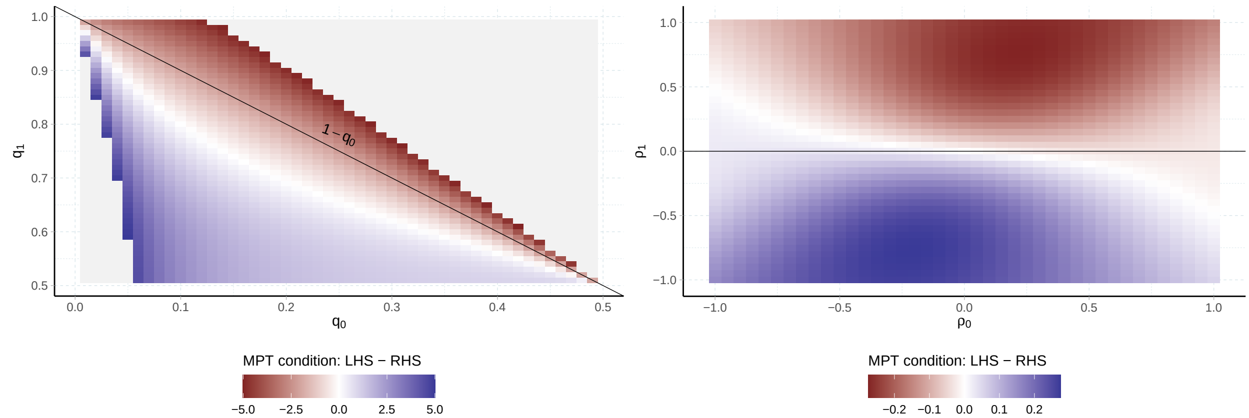
$$\Pr(UP = 1|IQ_C = 0) < 0.5$$

Panel A of Figure D.2 shows the simulation results in the binary intelligence case. When parallel trends assumption in Equation (6) holds, the difference between the left- and right-hand side is zero. The figure, therefore, plots the average value of this difference for each combination of persistence parameters q_0 and q_1 (averaging across all plausible values of u_0 and u_1). The cells with values close to 0 (coloured white) are the parameter combinations that on average are closest to satisfy the parallel trends assumption. The black line traces the parameter combinations that imply constant persistence of intelligence; values below the line corresopnd to decreasing and above - increasing persistence of intelligence. Thus, the numerical analysis shows that the parallel trends condition tends to hold when intergenerational persistence is slightly stronger at the bottom of the intelligence score distribution.

A similar analysis can be done in the case of continuous intelligence score. The continuous form of the parallel trends assumption in terms of parental intelligence can be written as

$$\frac{\text{Cov}(IQ_C, IQ_P|UP = 1)}{\text{Var}(IQ_C|UP = 1)} = \frac{\text{Cov}(IQ_C, IQ_P|UP = 0)}{\text{Var}(IQ_C|UP = 0)} \tag{7}$$

To analyse the condition in Equation (7), I need to specify the distribution of the parental intelligence score and two CEFs: $\mathbb{E}(IQ_C|IQ_P)$ and $\mathbb{E}(UP|IQ_P) = \Pr(U = 1|IQ_P)$. I assume that parental intelligence is drawn from a standard normal distribution $IQ_P \sim \mathcal{N}(0, 1)$. I



(a) Binary intelligence **(b) Continuous intelligence**

Notes: The figure plots the average value of parallel trends condition for each combination of persistence parameters in discrete (panel A) and continuous (panel B) intelligence cases. The black line corresponds to constant persistence frontier. Parameter combinations below the black line imply that persistence decreases with intelligence, and those above - that persistence increases with intelligence.

Figure D.2: parallel trends and intergenerational persistence of intelligence

also assume that intergenerational process on intelligence follows an AR(1) process, where persistence parameter is itself a function of parental intelligence.

$$IQ_C = \rho(IQ_P)IQ_P + \nu$$

I parametrise both the persistence parameter and the conditional unemployment probability as linear functions of intelligence

$$\begin{aligned} \rho(IQ_P) &= \rho_0 + \rho_1 IQ_P \\ \Pr(U = 1|IQ_P) &= \mu_0 + \mu_1 IQ_P \end{aligned}$$

I perform simulations for combinations of $\rho_0, \rho_1 \in [-1, 1]$. Positive ρ_0 implies positive persistence of intelligence at the mean. The parameter ρ_1 determines heterogeneity of the persistence: $\rho_1 = 0$ is a case of constant persistence and $\rho_1 < 0$ ($\rho_1 > 0$) describes decreasing (increasing) persistence of intelligence. For expositional simplicity, I fix the parameters $\mu_0 = 0.15$ and $\mu_1 = -0.05$, i.e., unemployment rate is 15% at the mean intelligence score and drops to zero for parents with intelligence score 3 sd above the mean.

The results of the simulation are shown in Panel B of Figure D.2 and are similar to those in the discrete case. The parallel trends assumption tends to hold when intergenerational persistence is stronger at the bottom of the intelligence score distribution, assuming positive persistence at the mean.

In addition to numerical analysis, some empirical evidence on intergenerational persistence can be glimpsed from the BCS70 dataset. The dataset includes both cognitive assessment of cohort members (parents) and their children (see Online Appendix B for more details). I divide parent-child pairs according to the age of child at the time of assessment: and . In

Table D.3: Intergenerational persistence of intelligence in the BCS70

	Children's age				
	3-5	6-8	9-11	12-14	15-16
IQ_P	0.177	0.075	0.114	0.203	0.039
	(0.037)	(0.039)	(0.057)	(0.077)	(0.115)
IQ_P^2	0.021	-0.051	0.048	-0.038	-0.111
	(0.025)	(0.026)	(0.040)	(0.053)	(0.074)
Const.	-0.034	0.090	-0.018	0.064	0.134
	(0.040)	(0.041)	(0.052)	(0.068)	(0.122)
Obs.	891	773	514	306	86

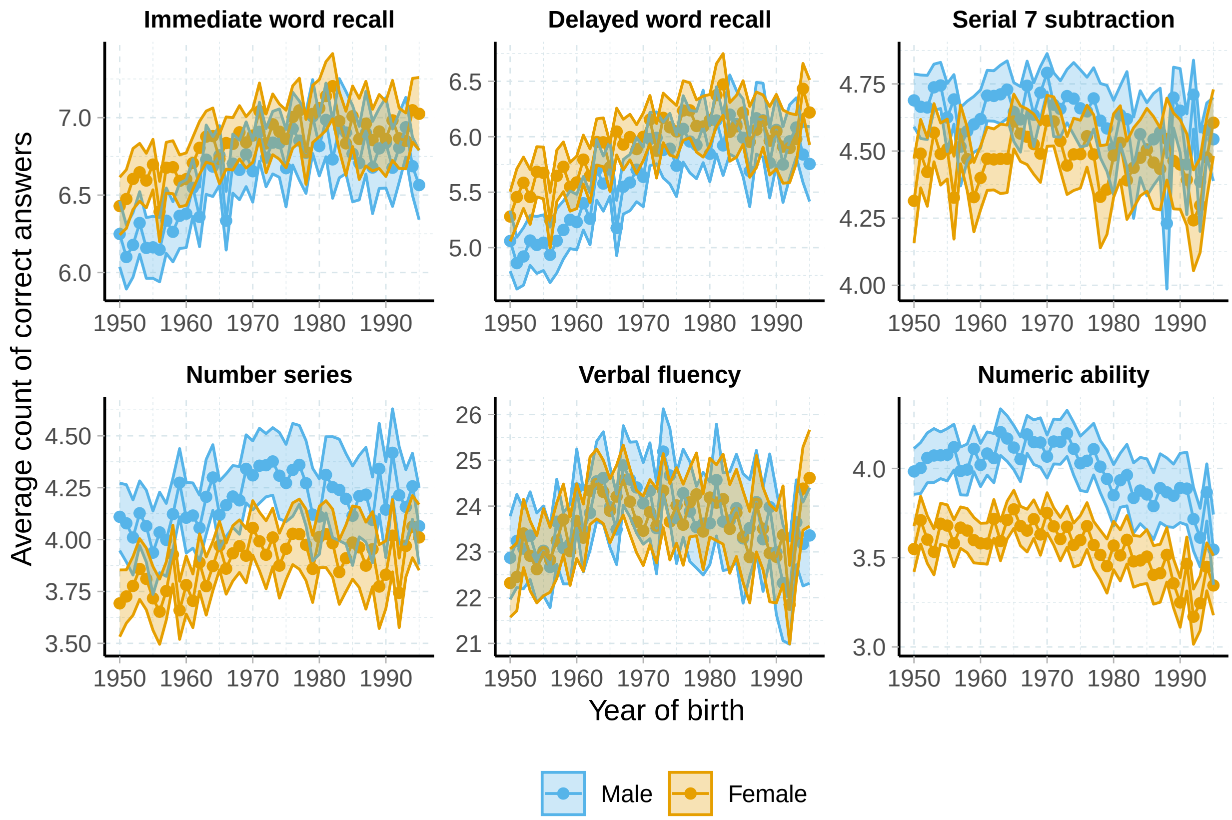
Notes: The table reports estimation results from unweighted regressions of children's standardized intelligence score on a quadratic polynomial of parents' standardized intelligence score. The sample consists of original cohort members surveyed at age 34 with children between ages 3 and 16 at the time of survey and given consent for cognitive assessment of children. The sample includes 2,570 parent-child pairs, which were divided into five groups based on children's age at the time of assessment. Parents' intelligence IQ_P is the score from the third wave when they were 10 years old. Persistence was estimated separately in each age group. Standard errors reported in parentheses.

each of these age groups, I regress children's standardized intelligence score on a quadratic polynomial of parents' intelligence score measured at the time parents were 10 years old. The results are shown in Table D.3. On average persistence is positive, consistent with the existing evidence in the literature. The results also suggest that persistence may be slightly decreasing with intelligence. However, this result should be taken with a grain of salt in view of small sample size and potentially non-random sample attrition, response to cognitive assessment and fertility outcomes.

A recent paper by Hanushek et al. (2021) documents the intergenerational transmission of skills along the entire distribution. In particular, the authors report a linear relationship between skills of parents and children with a positive slope at 0.091 (se 0.005). Thus, their findings suggest that skills are persistent across generation, but that persistence is constant across the distribution of skills. These parameters are consistent with the range of parameters under which the parallel trends assumption holds presented in Figure D.2b.

In sum, all pieces of evidence suggest the parallel trends assumption is not unreasonable. Tables D.1 and D.2 show that selection bias measured in terms of the observed pre-determined characteristics do not vary with intelligence of children. The analysis in this section addresses the concern that intergenerational process on intelligence and its correlation with economic outcomes may have on the identification strategy. I show that (i) these factors may indeed pose a threat to identification; (ii) a world with moderate positive intergenerational correlation, the parallel trend assumption is satisfied when persistence is constant; (iii) evidence from existing literature and parent-child pairs in the BCS70 dataset are consistent with the previous statement.

Appendix E Intelligence



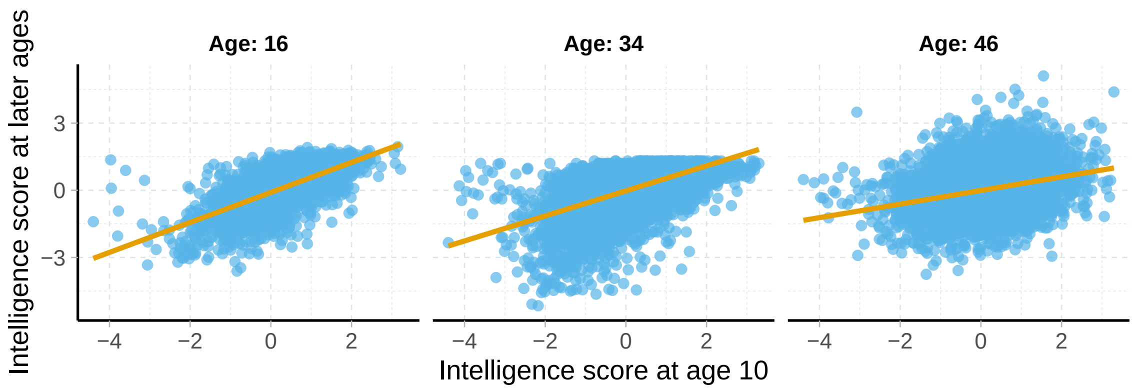
Notes: The figure plots the average raw test scores in each test by year of birth and gender of respondents. The shaded areas correspond to 95% confidence interval. The statistics are weighted by the cross-sectional response weights.

Figure E.1: Cognitive test results

Appendix E.1 Relative stability of intelligence over the life-cycle

There might also be a concern about the intelligence score in the UKHLS because it is measured at the time of the survey, possibly decades after the exposure to parental unemployment. That is, there is a possibility that intelligence score I use may not reflect well the intelligence children had at the age of 14. For example, if the intelligence measured in adulthood is not correlated with the score in childhood, the estimator of interest β_3 is biased towards zero to an extent that variation in intelligence is a pure noise. If this is the case, then the estimates presented in Tables 3 and 5 provide lower bounds for the magnitudes of differential impacts of parental unemployment across intelligence distribution. Below I discuss the existing evidence on the correlation between intelligence at different stages of life, which can help understand the extent to which the estimates are biased by measurement error.

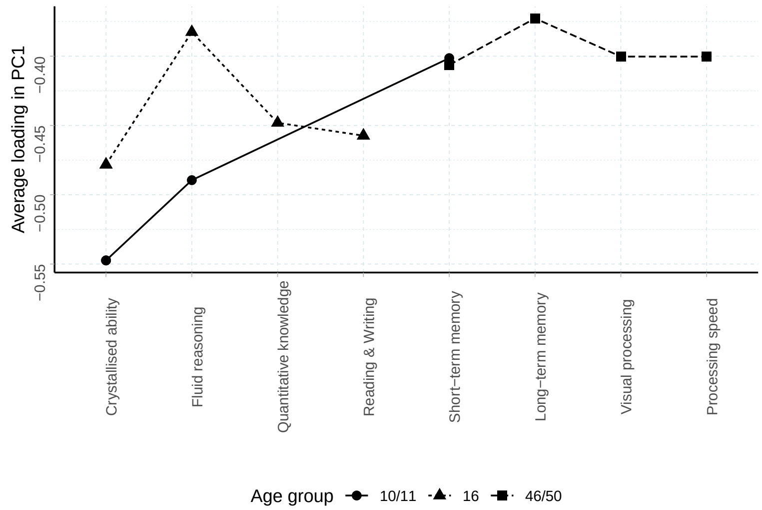
By using intelligence score measured later in life I am implicitly assuming that relative position of children along the distribution remains stable over time: a smarter child is also a smarter adult. Of course, the level of skills does not stay constant over the life cycle (Salthouse 2010). But the crucial point is that the relative position of individuals along the distribution of intelligence remains stable. There is evidence that large part of skill formation process is concentrated in certain periods of life (Cunha and Heckman 2007) with development of cognitive skills taking place by age 10 (Hopkins and Bracht 1975). Given that cognitive tests in the UKHLS measure cognitive function as opposed to achievement tests, the intelligence score is expected to stabilize at ages 8-10 (Cunha and Heckman 2007). Psychometric literature offers a more direct evidence in support of this assumption. Analysing population of Scottish cohorts born in 1921 and 1936 Deary (2014) estimates, conservatively, that about half of differences in intelligence score at age 70 can be traced back to relative standing in the distribution at age 11.



Notes: The figure plots the scatterplot of standardized intelligence scores at ages 16 and 46 against the score at age 10. Intelligence scores are constructed using first principal component standardized to zero mean and unit variance. The fitted linear regression line is displayed on top of the scatterplot.

Figure E.2: Stability of intelligence score by ages

The UKHLS does not allow me to test this assumption as there is only a single set of cognitive ability test scores measured in wave 3. The BCS70, on the other hand, administered cognitive tests several times throughout life. For example, cognitive ability test scores are available at ages 5, 10, 16, 34, 42 and 46 in the BCS70. Using the tests at ages 10, 16, 34 and 46, I construct intelligence scores at these ages by extracting the first principal component. Figure E.2 shows that intelligence scores at later ages are positively correlated with the intelligence score at age 10. For example, a one standard deviation increase in intelligence score at age 10 is associated with 0.7 standard deviation increase in intelligence score at the age of 16. Figure E.2 also shows that by age 50 the correlation coefficient reduces to 0.3. However, this is likely to be a lower bound due to sample attrition and differences in test composition. The tests administered at various ages are necessarily different. Tests appropriate for 10-year-old children might be too easy for 50-year-old individuals. Potentially, variations in the scores across ages could reflect differences in test contents, even among tests measuring the same domain of cognitive ability. In addition to this, the cohort studies had different aims when testing children vs adults. For example, childhood tests were mostly examining the ability of children to solve new problems using their skills, while in adulthood they focused more on the ability of individuals to perform day-to-day tasks (Figure E.3). Therefore, the tests at different ages were measuring different domains, which could also explain lower correlation at later ages.



Notes: The plot shows cognitive domains of tests administered at different ages. On the y-axis I plot simple average of test scores' loadings in PC1 in a given domain and age group.

Figure E.3: Cognitive domains of tests by ages

Appendix E.2 Intelligence as outcome of parental unemployment

The causal interpretation of β_3 in Equation (3) relies on intelligence of children not being as well an outcome of parental unemployment. The reader might be sceptical of this assumption, especially in light of the recent evidence in Carneiro et al. (2021) showing that higher family income during adolescent years increases intelligence of children. I cannot directly test the assumption since the measure of parental unemployment in the UKHLS or the BCS70 is non-random and may be correlated with intelligence. Nevertheless, I argue that β_3 can still have a causal interpretation with slight adjustment and supporting evidence in Table D.2 remains valid.

Recall the definition of the parameter β_3 in the population regression Equation (1)

$$\begin{aligned}\beta_3 &= \frac{Cov(y, IQ|UP=1)}{Var(IQ|UP=1)} - \frac{Cov(y, IQ|UP=0)}{Var(IQ|UP=0)} = \\ &= \frac{Cov(y^1, IQ^1|UP=1)}{Var(IQ^1|UP=1)} - \frac{Cov(y^0, IQ^0|UP=0)}{Var(IQ^0|UP=0)} = \\ &= \underbrace{\frac{Cov(y^1 - y^0, IQ^1|UP=1)}{Var(IQ^1|UP=1)}}_{\text{Causal effect}} + \underbrace{\frac{Cov(y^0, IQ^1|UP=1)}{Var(IQ^1|UP=1)} - \frac{Cov(y^0, IQ^0|UP=0)}{Var(IQ^0|UP=0)}}_{\text{Selection bias}}\end{aligned}$$

The first term describes how causal effect of parental unemployment changes with intelligence of children evaluated among children whose parents were unemployed. The second term reflects the bias stemming from changes in the composition of the pool of individuals with and without unemployed parents. Note that if intelligence is indeed an outcome of parental unemployment, the bias term may not be equal to zero even if parental unemployment were randomly assigned.

There is a slight change in the causal effect: it is measuring the differential impact of parental unemployment as IQ^1 increases, instead of IQ. In other words, the estimator can only identify changes in the causal effect after parents get unemployed. Intelligence may have affected the outcomes of these children differently had their parents kept their jobs. The main goal of this paper is to investigate how parental unemployment effects vary across intelligence of children. For this purpose the change in the interpretation is a minor one. However, it restricts the ability to provide policy-relevant statement of what would have happened in the counterfactual world where the parents of the affected children stayed employed. The estimated results could still speak to that, if potential outcomes depend on IQ^1 in the same way as on IQ^0.

As before, the parameter β_3 identifies the causal effect, if parallel trends assumption holds. With intelligence possibly being an outcome variable itself, it is now more difficult to provide a succinct interpretation to the parallel trends assumption. Regardless, the supporting evidence presented in Table D.2 based on observed pre-determined characteristics in the BCS70 remain valid. Even permitting $IQ^0 \neq IQ^1$, the selection bias term is identical to the coefficient of the interaction between observed IQ and UP in a regression with pre-determined outcome y^0 as the dependent variable. If the parallel trends assumption holds, then the coefficient of the interaction term should be zero.

Appendix F Additional robustness checks

Appendix F.1 Measures of parental unemployment

Notes: The plot compares the average parental unemployment indicator in the UKHLS with aggregate unemployment rates in the UK. The shares in the UKHLS are weighted by individual cross-sectional weights. The two aggreage series are official unemployment rates from 1971 onwards and male unemployment rate in the age group 40-49 from 1983 onwards. The shaded areas correspond to recessions.

Figure F.1: Parental unemployment and aggregate economy

A potential concern with the current parental unemployment measure is recall bias since the parental employment status is self-reported by children years or decades later. To assess the severity of the recall bias I plot the share of individuals reporting an unemployed parent against aggregate unemployment rates in the corresponding years in Figure F.1. I use two aggregate unemployment rates for comparison: one in the entire population of the UK and another - among British males at the ages 40-49, a superset of population of fathers of 14-year-old children. Reassuringly, for most of the sample the share of people with unemployed parent is comparable to both of the aggregate series. But, rather unexpectedly, the series diverge for the younger cohorts: average parental unemployment is much higher in the UKHLS. These cohorts were about 23-26 years old at the time of the wave 3 in 2011-13. The bias might be related to their experience during the financial crisis in 2008-09. Regardless of the reason, I test the sensitivity of the analysis results to the exclusion of cohorts born in 1981 or later (turned 14 in 1995 or later) in Table F.1. The point estimates are largely similar to the baseline results, both qualitatively and quantitatively.

Table F.1: Robustness to unemployment measures

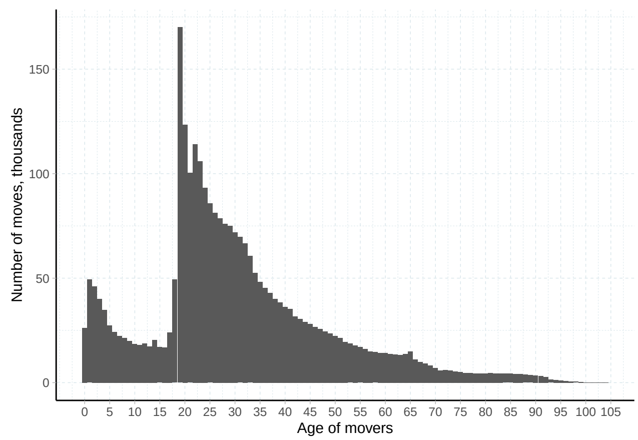
	Post-16 school	Degree	Work	%Δ earnings	%Δ hourly wage	Hours
Born before 1981						
Parent unemp	-0.058***	-0.007	-0.042***	-0.213***	-0.114***	-1.949***
	(0.017)	(0.016)	(0.015)	(0.052)	(0.032)	(0.605)
IQ	0.137***	0.137***	0.059***	0.326***	0.172***	2.021***
	(0.004)	(0.004)	(0.004)	(0.015)	(0.009)	(0.173)
Parent unemp × IQ	-0.029†	-0.017	0.049†††	0.138††	-0.039	1.383††
	(0.015)	(0.014)	(0.015)	(0.050)	(0.031)	(0.591)
Obs.	15,907	15,907	15,907	15,907	12,661	15,907
Outcome mean	0.36	0.28	0.80	2.85	0.17	27.35
Outcome sd	0.48	0.45	0.40	1.61	0.16	17.19
Unemployment incl. death and separation						
Parent unemp	-0.082***	-0.034***	-0.048***	-0.233***	-0.107***	-2.182***
	(0.012)	(0.011)	(0.011)	(0.037)	(0.023)	(0.413)
IQ	0.140***	0.132***	0.051***	0.291***	0.161***	1.830***
	(0.004)	(0.004)	(0.004)	(0.014)	(0.009)	(0.156)
Parent unemp × IQ	-0.043†††	-0.033†††	0.039†††	0.124†††	-0.030	1.406†††
	(0.010)	(0.009)	(0.011)	(0.034)	(0.020)	(0.388)
Obs.	20,329	20,329	20,329	20,329	15,655	20,329
Outcome mean	0.37	0.27	0.74	2.63	0.16	25.52
Outcome sd	0.48	0.44	0.44	1.65	0.15	17.68

†q < 0.1; ††q < 0.05; †††q < 0.01
*p < 0.1; **p < 0.05; ***p < 0.01
Notes:
The table reports estimation results from weighted regressions with dependent variables in columns. The first panel restricts the estimation sample to cohorts born before 1981. The second panel uses unemployment indicator where value of 1 includes unemployment, death and separation of parent. All regressions control for respondents' (gender, year of birth, country of birth, race, immigrant status) and parents' (highest educational qualifications and country of birth) characteristics. The IHS stands for inverse hyperbolic sine transformation. Standard errors clustered at the sampling unit are reported in parentheses. The p-values of the interaction coefficients are adjusted for multiple inference by controlling the false discovery rate (FDR) (Benjamini and Hochberg 1995).

Appendix F.2 Unemployment vs poverty

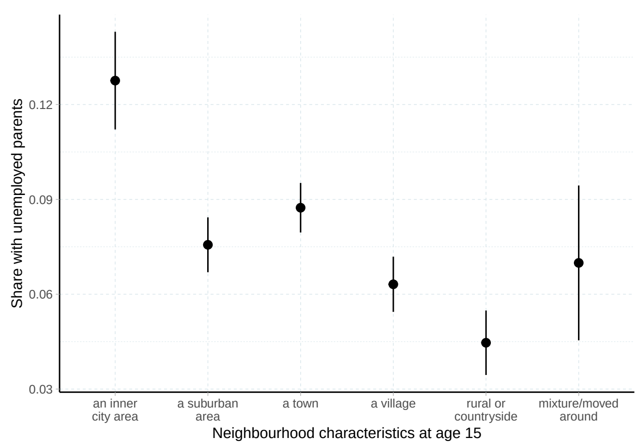
Another concern is that the current measure of parental unemployment does not differentiate between job loss and long-term non-participation in the labour force or poverty. The pre-determined characteristics of children and parents in $\mathbf{X}_i$ and $\mathbf{P}_i$, respectively, in Equation (1) should absorb some of the systematic differences in labour force participation rates.

Using limited information about family characteristics in childhood, I exploit the neighbourhoods where individuals were living at age 15 as an outcome variable. The idea is that neighbourhood characteristics are correlated with long-term household characteristics such as probability of re-employment (Vandecasteele and Fasang 2021) and poverty (van Ham et al. 2014). Relatively lower migration rates in early ages (Figure F.2) suggest that neighbourhood characteristics recorded at age 15 should be a good measure of areas individuals lived during their childhood and adolescence. Figure F.3 shows that many individuals with unemployed parents were concentrated among those living in inner city area at age 15.



Notes: The figure plots counts of moves between local authorities in the UK by age of movers. The counts include all moves occurring between June 2011 and June 2012. The counts exclude moves within Scotland and Northern Ireland, but include moves from England and Wales to Scotland and Northern Ireland. The counts also exclude moves within local authorities or in/out of the UK. The age is defined as age as of 30 June 2012. The dataset is obtained from the Office for National Statistics (ONS).

Figure F.2: Internal migration by age, UK 2012



Notes: The figure plots average parental unemployment rate by neighbourhood characteristics. The whiskers correspond to 95% confidence interval. The statistics are weighted by cross-sectional response weight.

Figure F.3: Neighbourhood characteristics at age 15 and parental unemployment

In Table F.2, I am repeating the main estimation with the indicator of living in inner city area as the dependent variable. Consistent with the graphical evidence, the probability of living in an inner city area increases if an individual's parent was not working and decreases with intelligence. However, the interaction term is close to zero suggesting that the differential impact of parental unemployment indicator is not driven by different composition of long-term characteristics of parents.

Table F.2: Neighbourhood characteristics at age 15, parental unemployment and IQ

	Inner city
Parent unemp	0.047***
	(0.011)
IQ	-0.015***
	(0.003)
Parent unemp × IQ	0.007
	(0.010)
Obs.	20,303

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: The table shows the results from regression of neighbourhood indicator at age 15 on parental unemployment and intelligence score. The regression controls for respondents' (gender, year of birth, country of birth, race, immigrant status) and parents' (highest educational qualifications and country of birth) characteristics. The regression is weighted by the cross-sectional response weight. Clustered standard errors are reported in parentheses.

Appendix F.3 Variations in exposure

In the main analysis, I restrict the sample to British-born individuals as a proxy for attending British schools. However, there may still be differences between the choice sets and institutional environments by ethnicity that interact with the way families and children respond to unemployment of parents. Furthermore, the institutional envrionments vary across countries in the UK. Therefore, parental unemployment may have different meaning depending on country of residence and ethnicity of houseuholds.

Table F.3: Robustness to variations in exposure to parental unemployment

	Post-16 school	Degree	Work	%Δ earnings	%Δ hourly wage	Hours
White British						
Parent unemp	-0.079***	-0.035***	-0.059***	-0.271***	-0.115***	-2.683***
	(0.014)	(0.013)	(0.014)	(0.048)	(0.029)	(0.542)
IQ	0.140***	0.131***	0.051***	0.289***	0.162***	1.788***
	(0.004)	(0.004)	(0.004)	(0.014)	(0.009)	(0.157)
Parent unemp × IQ	-0.035††	-0.039†††	0.052†††	0.145†††	-0.050†	1.703†††
	(0.013)	(0.011)	(0.014)	(0.044)	(0.028)	(0.497)
Obs.	18,176	18,176	18,176	18,176	14,209	18,176
Outcome mean	0.36	0.27	0.75	2.68	0.16	26.03
Outcome sd	0.48	0.44	0.43	1.63	0.16	17.54
Born in England						
Parent unemp	-0.080***	-0.036**	-0.055***	-0.264***	-0.123***	-2.690***
	(0.016)	(0.016)	(0.016)	(0.050)	(0.031)	(0.614)
IQ	0.135***	0.130***	0.051***	0.292***	0.158***	1.875***
	(0.004)	(0.004)	(0.005)	(0.015)	(0.009)	(0.179)
Parent unemp × IQ	-0.034††	-0.035††	0.055†††	0.148†††	-0.045	1.634†††
	(0.014)	(0.013)	(0.015)	(0.045)	(0.030)	(0.547)

Table F.3: Robustness to variations in exposure to parental unemployment *(continued)*

	Post-16 school	Degree	Work	%Δ earnings	%Δ hourly wage	Hours
Obs.	15,222	15,222	15,222	15,222	11,742	15,222
Outcome mean	0.35	0.28	0.75	2.66	0.16	25.83
Outcome sd	0.48	0.45	0.44	1.64	0.16	17.57
Born in Wales						
Parent unemp	-0.095	-0.040	-0.095	-0.332*	-0.049	-2.391
	(0.074)	(0.056)	(0.080)	(0.197)	(0.067)	(3.228)
IQ	0.139***	0.131***	0.060***	0.301***	0.228***	1.830**
	(0.020)	(0.017)	(0.021)	(0.048)	(0.051)	(0.825)
Parent unemp × IQ	-0.045	-0.060	0.031	0.171	-0.134	2.670
	(0.053)	(0.042)	(0.070)	(0.148)	(0.078)	(2.032)
Obs.	1,337	1,337	1,337	1,337	1,003	1,337
Outcome mean	0.37	0.23	0.72	2.53	0.15	25.34
Outcome sd	0.48	0.42	0.45	1.67	0.15	18.23
Born in Scotland						
Parent unemp	-0.076	-0.047	-0.078	-0.350***	-0.085	-3.262
	(0.057)	(0.051)	(0.053)	(0.134)	(0.071)	(2.022)
IQ	0.170***	0.141***	0.053***	0.327***	0.171***	1.681**
	(0.016)	(0.014)	(0.017)	(0.046)	(0.028)	(0.760)
Parent unemp × IQ	-0.012	0.001	0.044	0.098	-0.181††	2.079
	(0.063)	(0.046)	(0.060)	(0.139)	(0.068)	(2.125)
Obs.	1,927	1,927	1,927	1,926	1,502	1,927
Outcome mean	0.48	0.26	0.74	2.68	0.16	25.95
Outcome sd	0.50	0.44	0.44	1.63	0.11	17.80
Born in NI						
Parent unemp	-0.042	-0.024	-0.082	-0.290*	0.007	-2.695
	(0.157)	(0.125)	(0.147)	(0.165)	(0.091)	(5.458)
IQ	0.149***	0.109**	0.100*	0.434***	0.142***	3.604*
	(0.055)	(0.047)	(0.052)	(0.051)	(0.020)	(1.950)
Parent unemp × IQ	-0.043	0.000	-0.089	-0.255	0.104	-3.186
	(0.144)	(0.120)	(0.116)	(0.146)	(0.093)	(4.261)
Obs.	1,436	1,436	1,436	1,434	1,091	1,436
Outcome mean	0.51	0.26	0.73	2.58	0.14	24.83
Outcome sd	0.50	0.44	0.45	1.63	0.10	17.34

†q < 0.1; ††q < 0.05; †††q < 0.01
*p < 0.1; **p < 0.05; ***p < 0.01
Notes:
The table reports estimation results from weighted regressions with dependent variables in columns. The first panel restricts the estimation sample to cohorts born before 1981. The second panel uses unemployment indicator where value of 1 includes unemployment, death and separation of parent. All regressions control for respondents' (gender, year of birth, country of birth, race, immigrant status) and parents' (highest educational qualifications and country of birth) characteristics. The IHS stands for inverse hyperbolic sine transformation. Standard errors clustered at the sampling unit are reported in parentheses. The p-values of the interaction coefficients are adjusted for multiple inference by controlling the false discovery rate (FDR) (Benjamini and Hochberg 1995).

Therefore, I repeat the estimations in the sample that is restricted to white British individuals only in the first panel of Table F.3. The results are very similar to the main results reported in Tables 3 and 5.

Another possible concern is that institutional environment is not uniform within the UK. For example, Online Appendix A has touched upon differences in high-school exams and university admissions between England and Scotland. Therefore, the second through fifth panels of Table F.3, I repeat the estimations separately by UK country of birth: England, Scotland, Wales and Northern Ireland (NI). Again the estimates among individuals born in England and Wales are very similar to the main results. Interestingly, the estimates of the interaction effect on educational outcomes are smaller in magnitude when I restrict the estimation sample to those born in Scotland. This result is consistent with education system in Scotland being less selective. The results among individuals born in Northern Ireland are the most surprising. Here, higher intelligence individuals exposed to unemployed parents are relatively unaffected in terms of educational outcomes, but are heavily penalized in the labour market.

Appendix F.4 Replication in the BCS70

Finally, I attempt to replicate the main analysis in the BCS70 and compare it to the effects estimated using only individuals born in 1970 in the UKHLS (Table F.4). The first panel repeats the estimation in the UKHLS subsample of individuals born in 1970 (baseline for comparison). These results are largely similar to the main results reported in Tables 3 and 5. Second through fifth panels report replicated estimates in the BCS70 surveys at ages 26, 30, 34 and 38, respectively. These estimates are consistent with the main results: higher intelligence makes educational outcomes of children more vulnerable to losses due to parental unemployment, but helps narrow the gap in labour market outcomes. The effects on labour market outcomes also appear to be increasing in age, consistent with the employer-learning theory.

Table F.4: Replication in the BCS70

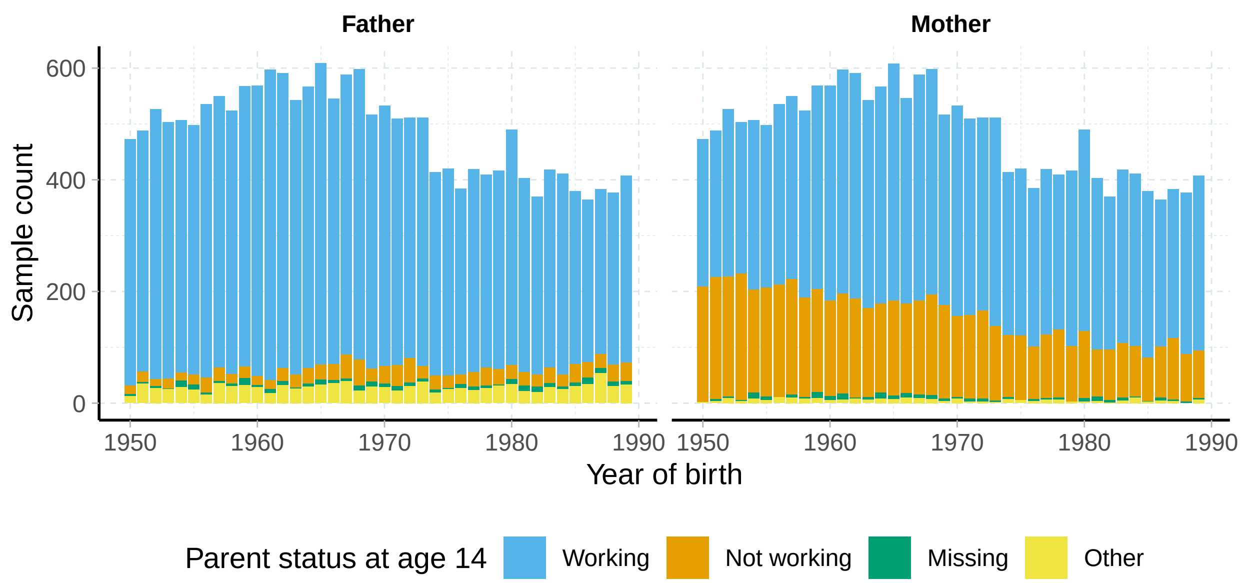
	Post-16 school	Degree	Work	%Δ earnings	%Δ current job rank
UKHLS sample born in 1970					
Parent unemp	-0.026	0.127***	-0.007	-0.079	0.197
	(0.034)	(0.017)	(0.016)	(0.236)	(0.189)
IQ	0.129***	0.160***	0.031***	0.267***	0.227***
	(0.009)	(0.008)	(0.007)	(0.079)	(0.079)
Parent unemp × IQ	-0.051	-0.004	0.106†††	0.197	0.367
	(0.026)	(0.014)	(0.016)	(0.222)	(0.194)
Obs.	578	578	578	578	578
BCS70 at age 26					
Parent unemp	-0.039	-0.044***	-0.146***	-0.564***	-0.014
	(0.024)	(0.013)	(0.030)	(0.113)	(0.065)
IQ	0.119***	0.096***	0.048***	0.234***	0.090***
	(0.007)	(0.006)	(0.009)	(0.030)	(0.017)

Table F.4: Replication in the BCS70 *(continued)*

	Post-16 school	Degree	Work	%Δ earnings	%Δ current job rank
Parent unemp × IQ	-0.055††	-0.072†††	0.028	0.078	0.012
	(0.020)	(0.011)	(0.027)	(0.089)	(0.055)
Obs.	5,029	4,901	5,063	4,780	1,920
BCS70 at age 30					
Parent unemp	-0.055*	-0.045***	-0.119***	-0.476***	-0.123
	(0.031)	(0.017)	(0.027)	(0.160)	(0.075)
IQ	0.141***	0.113***	0.026***	0.162***	0.143***
	(0.009)	(0.006)	(0.006)	(0.043)	(0.021)
Parent unemp × IQ	-0.026	-0.060†††	0.082††	0.280†	0.089
	(0.027)	(0.016)	(0.027)	(0.145)	(0.063)
Obs.	4,047	5,056	4,170	1,886	2,442
BCS70 at age 34					
Parent unemp		-0.023	-0.086***	-0.639***	-0.058
		(0.020)	(0.026)	(0.182)	(0.076)
IQ		0.102***	0.024***	0.205***	0.155***
		(0.006)	(0.006)	(0.054)	(0.026)
Parent unemp × IQ		-0.039†	0.087††	0.210	0.003
		(0.018)	(0.028)	(0.170)	(0.055)
Obs.		5,063	3,757	1,375	2,118
BCS70 at age 38					
Parent unemp		0.013	-0.044*	-0.190	-0.254
		(0.032)	(0.026)	(0.145)	(0.370)
IQ		0.135***	0.019***	0.253***	0.007
		(0.009)	(0.007)	(0.041)	(0.098)
Parent unemp × IQ		-0.005	0.023	-0.065	0.234
		(0.026)	(0.028)	(0.153)	(0.209)
Obs.		3,555	3,542	3,148	5,046

†q $<$ 0.1; ††q $<$ 0.05; †††q $<$ 0.01
*p $<$ 0.1; **p $<$ 0.05; ***p $<$ 0.01
Notes:
The table reports comparison of estimation results in UKHLS subsample of people born in 1970 and BCS70. Regressions in the UKHLS control for respondents' (gender, year of birth, country of birth, race, immigrant status) and parents' (highest educational qualifications and country of birth) characteristics. Regressions in the BCS70 control for respondents' (gender, country of birth) and parents' (country of birth and age left education) characteristics. The IHS stands for inverse hyperbolic sine transformation. Regressions in the UKHLS are weighted with cross-sectional response weight of wave 3. Regressions in the BCS70 are weighted with inverse probability of response (Mostafa and Wiggins 2014) at age 10, 16 and age of measurement reported in column. Standard errors are reported in parentheses and clustered at the sampling unit in the UKHLS.

Appendix G   Supplementary Figures and Tables



Notes: The figure plots distribution of UKHLS working sample by status of each parent. The counts are weighted by cross-sectional response weights.

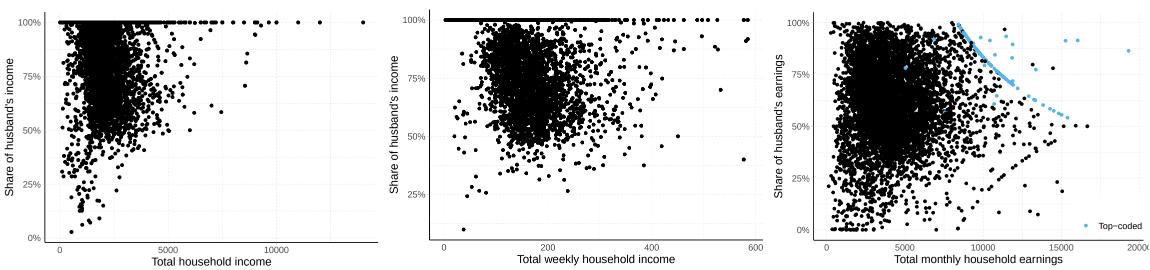
Figure G.1: Parental status at age 14

Table G.1: Heckman selection correction for realised labour-market outcomes

	Dependent variables			
	IHS earnings	IHS hourly wage	Hours	IHS current job rank
Parent unemp	-0.270***	-0.037***	-1.539***	-0.086***
	(0.064)	(0.009)	(0.431)	(0.016)
IQ	0.290***	0.046***	0.526**	0.129***
	(0.036)	(0.005)	(0.252)	(0.008)
Parent unemp × IQ	0.122**	0.010	0.697*	0.026*
	(0.061)	(0.009)	(0.410)	(0.015)
Obs.	20,307	20,307	20,307	20,307

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table reports coefficients from unweighted two-step Heckman selection regressions of labour-market outcomes. The selection equation is same as the regression equation for probability of work. All regressions control for respondents' (gender, year of birth, country of birth, race, immigrant status) and parents' (highest educational qualifications and country of birth) characteristics. The IHS stands for the inverse hyperbolic sine transformation. Standard errors are reported in parentheses.



(a) GHS 1972 **(b) GHS 1980** **(c) UKHLS 2011-13**

Notes: The figure plots share of husband's income in total household income in the General Household Survey from years 1972 and 1980 as well as in the UKHLS wave 3. The sample is restricted to households with both husband and wife present. Nominal earnings at the time of each survey are plotted on the x axis.

Figure G.2: Distribution of household income