# Does intelligence shield children from the effects of parental non-employment?\*

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July 31, 2024

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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 of children. The results suggest that loss of human capital investments into children is the driving mechanism. I find that higher intelligence exacerbates the losses in education, but helps narrow the gaps in labourmarket outcomes. I rationalise these findings using the skill formation and employer learning theories.

JEL classifications: I21, J24, J62

*Keywords*: parental non-employment, intelligence, education, earnings, human capital investments, employer learning

<sup>\*</sup>I would like to thank anonymous reviewers, Andrea Ichino, Giulio Zanella, Stephen Machin, Sule Alan, Thomas Crossley, Benjamín Villena-Roldán as well as the participants at the EUI Microeconometrics Working Group, the 34th EALE Conference, ASSA 2023 Annual Meeting and MEA/SOLE 2023 for useful comments.

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# 1 Introduction

The topic of how parental job loss affects children has been receiving 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 labourmarket outcomes of children. These effects are especially pronounced among children from disadvantaged backgrounds<sup>1</sup>. However, various papers propose different channels through which parental unemployment affects children. In this paper, I present new evidence on how intelligence of children can change 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). Therefore, if having non-working parents during teenage years affects children through stress, then intelligence can be expected to dampen the negative effects. On the other hand, the skill formation theory in Cunha and Heckman (2007) argues that human capital investments parents make into their children positively depend on the existing level of skills of children. The implication is that teenagers with high intelligence that lose these investments are the ones to suffer the most. Therefore, if parental unemployment acts through loss in human capital investments, then higher intelligence can exacerbate the negative effects.

To estimate how the effect of non-working parents on children differs by intelligence 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<sup>2</sup> of adult respondents and employment status of their parents at the time when respondents were 14 years old. This age is important in the context of the UK education system when children start in-depth preparations for GCSE exams. The selectivity of the education system in the UK means that past exams have high impact on admission to the next educational stage. Therefore, it can contribute to large and potentially lasting effects of non-working parents on trajectories of children, but also can make it easier to detect heterogeneity by intelligence.

The estimation strategy is inspired by the difference-in-differences (DiD) framework. Although the current setting differs from traditional time-varying treatment rollout in DiD, I use parental employment status as equivalent to treatment and children's intelligence scores as equivalent to time variables. Then, borrowing from the parallel trends assumption

<sup>&</sup>lt;sup>1</sup>Oreopoulos, Page, and Stevens (2008); Page, Stevens, and Lindo (2009)

<sup>&</sup>lt;sup>2</sup>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.

in DiD, I argue that the interaction between parental non-employment and intelligence can have a causal interpretation if (i) selection bias does not vary with intelligence and (ii) intelligence of children is not an outcome of parental non-employment. I provide empirical and numerical evidence in support of these assumptions. However, these are strong assumptions and may be violated in practice. In that case, I believe the estimated effects present interesting correlations that can motivate future causal analyses on this topic.

I present two key findings. First, educational outcomes of people with higher intelligence are more vulnerable to having non-employed parents. The gap in years of schooling widens, on average, by 0.8 months for every 1 standard deviation (sd) higher intelligence score. This result amounts to 15% of increase in schooling years attributed to raising the school-leaving age (Oreopoulos 2006). Furthermore, the gap in tertiary degree attainment widens by 3.6 percentage points (pp) for every 1 sd increase in the intelligence. This finding is consistent with the dynamic complementarity theory of Cunha and Heckman (2007). I also show that these additional losses are mainly borne by children of less-educated parents, which are likely also children from lower-income families. The economic theory suggests that only poor households adjust human capital investments made into children in response to income shocks (Mulligan 1997).

My second finding is that higher intelligence helps to bridge the gap in the labour-market outcomes. For example, the percent gap in earnings shrinks by 0.13 pp for every 1 sd increase in intelligence. This effect is, in part, mediated through higher labour supply, both on the extensive and intensive margins. The results also suggest that higher intelligence helps individuals who had non-working parents to find generally better-paying jobs and to be more likely to hold supervisory roles in their jobs<sup>3</sup>.

The two sets of findings suggest that, despite exacerbating the losses in educational achievements, high intelligence allows children of non-working parents to overcome these disadvantages over time. This result is consistent with the employer learning theory<sup>4</sup>, 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 related to productivity, such as intelligence, rises. The theory presents two testable implications. First, the effect of parental non-employment on initial labour-market outcomes of children should not vary by intelligence score. When individuals first enter the labour market, employers can only use their educational qualifications to form a belief about worker productivity. This means that

<sup>&</sup>lt;sup>3</sup>There may be other channels through which higher intelligence helps workers improve their labour market outcomes not considered in the present analysis, such as productivity and efficiency.

<sup>&</sup>lt;sup>4</sup>Farber and Gibbons (1996); Arcidiacono, Bayer, and Hizmo (2010); Altonji and Pierret (2001)

under-educated high-intelligence children of non-working parents are initially unable to distinguish themselves from job candidates with lower skills. Indeed, I find that the effect of parental non-employment on median earnings-based ranking of first jobs does not vary with intelligence of children. Nor there is differential impact on the probabilities of holding managerial or supervisory roles at their first jobs. Comparing to current jobs, I find that higher intelligence improves job ranking of workers with at least 10 years of experience. Second implication of the employer learning theory is that the mitigating effect of intelligence should increase with experience. Using a panel dimension of the UKHLS, I find that the age profiles are consistent with the second prediction.

In the context of the discussion about channels through which parental employment status 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 on educational outcomes offers another testable prediction: human capital investments are less dependent on existing skills at earlier ages. Using the auxiliary dataset, the British Cohort Study 1970, I show that the interaction parental non-employment and intelligence of children is more negative with age at which parental non-employment is measured. Another heterogeneity exercise is to compare non-employment effects of mothers and fathers. The idea is that fathers were traditionally primary earners, meaning their non-employment is associated with larger fall in familty income. And losses in human capital investments into children are likely proportional to overall income losses. I find that the main results mainly operate through father's employment status. Finally, I study whether the effects vary by children's gender. I do not find any statistically significant differences between responses of men and women, both before and after correction for multiple inference.

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 the Online Appendix G.1). Majority of the papers find large negative effects on educational outcomes<sup>5</sup> and small or zero effects on labour market outcomes of children<sup>6</sup>. 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. Second channel put forward in the literature is mental distress. This

<sup>&</sup>lt;sup>5</sup>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)

<sup>&</sup>lt;sup>6</sup>Mörk, Sjögren, and Svaleryd (2019); Hilger (2016); Page, Stevens, and Lindo (2009); Bratberg, Nilsen, and Vaage (2008)

paper contributes to the discussion on mechanisms of parental unemployment effects by exploiting different interactions of these channels with the intelligence of children. The results suggest that losses in human capital investments parents make into children 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 studying directly 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. 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.

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 the intelligence of children. Section 3 describes the datasets and variables used in the analysis. Section 4 reviews the empirical strategy and Section 5 presents the main results. In Section 7 I examine the robustness of findings. Section 8 provides additional heterogeneity analysis in the context of the proposed mechanisms of parental unemployment effects. Finally, Section 9 concludes the paper.

# 2 Parental unemployment and children's outcomes

The analysis in this paper uses parental employment status 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 non-working parents. 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 the Online Appendix A I describe the education system of the UK and argue that selectivity of the university admission policies can contribute to large and potentially lasting effect of parental non-employment on children's outcomes. It can also make the heterogeneity by intelligence of children 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-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<sup>7</sup>. How is loss of educational investments expected to interact with intelligence of children? I turn to the skill formation theory of Cunha and Heckman (2007), in particular, the dynamic complementarity. The theory suggests that returns to the human capital investments into children depend both on age of the child and her 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 having a non-working parent affects children through loss of human capital investments, children with high intelligence can be expected to suffer the most.

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,

<sup>&</sup>lt;sup>7</sup>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.



*Note:* 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

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 psychology literature, Masten et al. (1999) and Gale et al. (2009) find that intelligence acts as a protective factor against stress. Santarnecchi, Rossi, and Rossi (2015) report that brain functions of individuals with higher intelligence are more resilient to shocks. These are also consistent with the argument of cross-productivity between cognitive and non-cognitive skills in the skill formation theory (Cunha and Heckman 2007). If parental non-employment mainly operates through psychological distress, we can expect intelligence to dampen the negative effects.

Finally, joblessness 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 parents with lower educational qualifications and with lower aspirations towards educational attainment of their children. There is also some evidence that parents' aspirations are more positive and more accurate when their child's intelligence is higher (Murayama et al. 2016). This might suggest again that higher intelligence can protect children from lower education and career aspirations that may accompany parental non-employment.

# 3 Data

The main data source I am using is the UK Household Longitudinal Study (UKHLS)<sup>8</sup>, also known as the Understanding Society, the largest household panel study in the UK. The study covers a wide range of topics, including measures of cognitive ability and parental employment. The original study participants were sampled randomly from the UK population in 2009 and their households are followed each year.

The analysis in this paper relies on the data from wave 3 covering 49 692 individuals surveyed between 2011 and 2013. Crucially, during the third wave the UKHLS conducted cognitive tests among all adult participants<sup>9</sup>.

I restrict the analysis sample to individuals who (i) had non-zero response weight<sup>10</sup> (), (ii) were born in the UK (37 487), (iii) were born between 1950 and 1995 (26 895), (iv) finished school (25 387), (v) complied with compulsory schooling laws (23 335), (vi) were not institutionalised at age  $14^{11}$  (22 930), and (vii) had non-missing highest educational qualification information (22 779). Out of the remaining 22 779 individuals 1 571 have missing information about cognitive test scores. Table G.1 in the Online Appendix compares descriptive statistics in the analysis sample before and after removing such individuals. Although they differ significantly from the participants who took the tests, relatively few observations have missing cognitive scores. Therefore, their exclusion has a minimal impact on the characteristics of the working sample.

I also present supporting evidence using the British Cohort Study 1970  $(BCS70)^{12}$ , a longitudinal survey of individuals born in a week of 1970 in Great Britain. Compared to the UKHLS, the BCS70 offers a more extensive set of outcomes at birth and childhood as well as repeated measurements of cognitive skills throughout childhood. However, the BCS70 is a much smaller dataset, especially taking into account sample attrition over time. Following Mostafa and Wiggins (2014), I compute inverse probability weights to

<sup>&</sup>lt;sup>8</sup>University of Essex, Institute for Social and Economic Research (UKHLS)

<sup>&</sup>lt;sup>9</sup>Alternative strategy could be to focus on children of the UKHLS respondents. The UKHLS has collected information on all children ever observed in the study into a single dataset with nearly 20K children. The benefit of this strategy is that family information is directly observed in the survey. Children were also given Raven Progressive Matrices test in wave 10, which can be used to compute intelligence scores. However, out of 20K children in the data a little more than 2K have non-missing Raven scores and only around 700 of them are observed past the age of 16.

<sup>&</sup>lt;sup>10</sup>At each wave, the UKHLS includes a set of longitudinal and cross-sectional weights that account for initial sampling probabilities as well as unequal response probabilities over time. In addition, the dataset includes information on sampling unit and strata that altogether allow me to account for survey design in my analysis.

<sup>&</sup>lt;sup>11</sup>Dropping respondents institutionalised at age 14 from the sample makes sure that exposure to parental employment status can have an impact on individuals' choices. 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.

<sup>&</sup>lt;sup>12</sup>Chamberlain, University of London, Institute of Education, Centre for Longitudinal Studies, and Chamberlain (1970 British Cohort Study: Birth and 22-Month Subsample, 1970-1972)

account for attrition. For a more detailed description of the dataset, working sample and variables see Online Appendix B.

#### **3.1** Parental non-employment

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, not working, deceased or not living with them. For the main analysis, I construct parental non-employment indicator equal to 1 if they were not working, 0 if they were working and missing otherwise<sup>13</sup>. Thus, 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 information; if missing, I use mother's status<sup>14</sup>. The final parental nonemployment indicator has 901 missing observations. Table 1 presents descriptive statistics in the working sample with non-missing parental employment status and estimated mean differences in the subsample with missing parental status. Observations with missing parental status are predominantly under 20 years old, most of which were in full-time education at the time. After removing these observations, there are almost no significant differences between missing and non-missing observations.

The constructed parental non-employment indicator may include unemployed parents as well as more long-term inactive (for example, disabled, retired or stay-at-home parents). Unfortunately, the information collected in the survey is insufficient to disentangle between various reasons for non-employment. Figure G.2 in the Online Appendix shows that during the years when most of the sample was 14 years old between half and two-thirds of non-employed adults aged 40-50 were unemployed looking for jobs. It is clear, therefore, that parental non-employment is not an exogenous event. In Section 4 I discuss how this affects the empirical strategy adopted in the current study.

Since parental employment status is self-reported by the respondents, I compare it to various aggregate measures of unemployment in Figure F.1 in the Online Appendix. Somewhat surprisingly, the discrepancies are only observed among younger cohorts. In Section 7 I show that the results remain unchanged when cohorts with large discrepancies are removed from the estimation sample.

 $<sup>^{13}</sup>$ In Online Appendix F.1 I show that the results are robust to the inclusion of parental death and separation categories into the non-employment indicator.

<sup>&</sup>lt;sup>14</sup>At the time when the respondents in the analysis sample were growing up, fathers were predominantly primary earners in the household (Figure G.1).

	Non-missing parental status			Missing parental status					
				A	.11	Ov	ver 20		
Variable	Mean	SD	N	Diff	SE	Diff	SE		
Age	41.067	12.324	20307	$-21.084^{\dagger\dagger\dagger}$	0.354	0.571	1.124		
Female	0.513	0.500	20307	$-0.082^{\dagger\dagger\dagger}$	0.020	-0.084	0.051		
British	0.941	0.235	20230	$-0.075^{\dagger\dagger\dagger}$	0.015	-0.034	0.030		
Parents w/ degree	0.145	0.352	17079	$0.135^{\dagger\dagger\dagger}$	0.027	0.058	0.052		
School-leaving age	16.576	1.059	20302	$0.985^{\dagger\dagger\dagger}$	0.092	-0.933	0.387		
Post-16 school	0.362	0.481	20307	$0.161^{\dagger\dagger\dagger}$	0.020	-0.106	0.046		
Degree	0.277	0.448	20307	$-0.244^{\dagger\dagger\dagger}$	0.008	-0.059	0.048		
Work	0.759	0.428	20307	$-0.56^{\dagger\dagger\dagger}$	0.016	0.056	0.037		
Self empl	0.095	0.293	20307	$-0.081^{\dagger\dagger\dagger}$	0.005	0.005	0.031		
IHS earnings	2.705	1.619	20307	$-1.774^{\dagger\dagger\dagger}$	0.052	0.165	0.154		
Earn > 0	0.782	0.413	20307	$-0.33^{\dagger\dagger\dagger}$	0.021	0.039	0.037		
Earn > med	0.514	0.500	20307	$-0.14^{\dagger\dagger\dagger}$	0.019	-0.029	0.057		
Log current job rank	7.716	0.408	15829	$-0.667^{\dagger\dagger\dagger}$	0.040	-0.014	0.037		
Log first job rank	2.506	0.264	15852	$0.052^{\dagger\dagger\dagger}$	0.017	-0.056	0.035		

Table 1: UKHLS descriptive statistics and missing parental status

 $^{\dagger}{\rm q}<0.1;\,^{\dagger\dagger}{\rm q}<0.05;\,^{\dagger\dagger\dagger}{\rm q}<0.01$  based on FDR adjusted q-values

*Note:* The table reports descriptive statistics in the working dataset by missingness of parental employment status. For the definition of analysis sample, see Section 3. The first three columns of the table report statistics for the analysis sample with non-missing parental employment. Next two columns provide difference in means among observations with missing parental status and standard error. Last two columns provide similar difference in means, but using people aged over 20. The estimated differences are reported with significance stars that are based on p-values adjusted for multiple hypothesis controlling for the false discovery rate (Benjamini and Hochberg 1995).

## 3.2 Intelligence score

In wave 3, the UKHLS conducted cognitive ability tests among all adult respondents. The five cognitive tests - word recall (immediate and delayed), 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 plotted in Figure E.1 in the Online Appendix. The figure also shows that there are gender differences in test performances. 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 non-employment and their intelligence score. Therefore, the above

normalisation of intelligence score ensures that individuals are compared relative to their own peer group, in terms of birth cohort and gender.

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.

		Dependent variables								
	Degree	Work	IHS earnings	Log current job rank						
IQ	0.145	0.059	0.330	0.096						
	(0.003)	(0.004)	(0.014)	(0.004)						
Const.	0.267	0.735	2.630	7.697						
	(0.004)	(0.004)	(0.014)	(0.004)						
Obs.	21 208	21 208	21 208	16 126						

Table 2: Average outcomes	by	intelligence	score
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*Note:* The table reports simple regression coefficients from weighted regressions of dependent variables in columns on intelligence score. The IHS stands for inverse hyperbolic sine transformation. For large values of untransformed dependent variable, the estimated coefficients are approximately equivalent to semi-elasticities. For exact conversion to elasticities see Bellemare and Wichman (2020). Standard errors clustered at the sampling unit are reported in parentheses.

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 implicitly assuming that relative position of an individual along the intelligence distribution remains unchanged over time. In the Online Appendix E I discuss the existing literature studying this question, which typically supports the claim. 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 highest qualification data, I construct two indicator variables. First, a *degree* indicator equal to one if have a tertiary degree or higher and zero otherwise. The base

group in this indicator includes people who stopped at school level and those who have some post-compulsory qualifications from non-degree programs. Second indicator variable (*post-16 school*) is equal to one if the respondent stayed in education past the compulsory age of 16 and zero otherwise.

#### 3.4 Labour market outcomes

In the main analysis, I use the outcomes reported during wave 3 of the UKHLS corresponding to years 2011-13. 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 non-employment. The survey also includes information about usual *hours* worked in a week among employed and self-employed respondents. Table 1 shows that nearly a quarter of the sample is not working and, thus, have missing hours data. I replace missing hours with zero for the main analysis. In Online Appendix 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 may be affected by parental non-employment and intelligence<sup>15</sup>.

The survey has information on monthly labour earnings. I also compute hourly wages computed by dividing earnings with hours worked. I deflate both earnings and hourly wages by the consumer price index excluding rent, maintenance and water charges (Fisher et al. 2019). 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  $\operatorname{arcsinh}(x) = \ln(x + \sqrt{x^2 + 1})$ , which allows zero and negative values of transformed variable. For large values of x, the coefficients from a regression of  $\operatorname{arcsinh}(x)$  are approximately equivalent to semi-elasticities. But I also compute exact semi-elasticities following Bellemare and Wichman (2020).

Finally, the dataset contains occupational codes from current, last and first jobs for each individual. I rank these job codes according to real median annual gross earnings of workers from same birth cohorts at corresponding job groups<sup>16</sup>. Thus, the rankings show how well paid someone's job is among similar workers. I describe the ranking procedure in more detail in the Online Appendix C. Table 1 and Figure C.1 in the Online Appendix show that people typically start at lower paying jobs and move to higher paying jobs over time.

 $<sup>^{15}{\</sup>rm Since~I}$  do not have additional exogenous variation in the extensive margin, the identification in the two-step procedure rests solely on non-linearity of the regression function.

<sup>&</sup>lt;sup>16</sup>Due to data availability and inconsistency of job classifications over time, I aggregate all job codes to 1-digit level (major groups) before merging with median earnings.

## 3.5 Descriptive evidence



*Note:* The figure plots parental non-employment gaps in outcome variables in each panel by terciles of intelligence score. Parental non-employment gap is computed as the difference in sample mean among individuals with non-working parents relative to those with working parents at age 14.

#### Figure 2: Average gap in outcomes due to parental unemployment by intelligence terciles

Before turning to the estimation strategy and results, I examine graphical evidence. Figure 2 plots the gap between outcomes of children with non-working parents relative to those with working parents across intelligence score terciles. First, the figure suggests that there is a discount associated with parental non-employment: the average outcomes are typically lower among children whose parents were not working. 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 non-employment.

# 4 Empirical strategy

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

$$y_i = \beta_0 + \beta_1 U P_i + \beta_2 I Q_i + \beta_3 U P_i \times I Q_i + \beta_4 \mathbf{X}_i + \beta_5 \mathbf{P}_i + v_i \tag{1}$$

where  $y_i$  is outcome of individual i,  $UP_i$  is the indicator if a parent was not working 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,  $\beta_1$  captures the gap in outcomes of children with non-employed parents at average intelligence and  $\beta_2$  captures linear effect of higher intelligence on outcomes among children whose parents stayed employed. The coefficient of interest  $\beta_3$  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 in Equation (1) is similar to a difference-in-differences regression. I exploit the similarity to argue that the interaction coefficient  $\beta_3$  can have a causal interpretation. Recall that a typical difference-in-differences setup involves some treatment implemented at time  $t_0$  for a subset of population. The estimation then compares how outcomes changed before and after  $t_0$  among treated versus control units. The identifying assumption in a standard setting is that outcomes of treated units would have evolved over time in the same way as did outcomes of control observations, also known as parallel trends assumption.

In the context of this paper, parental non-employment indicator is equivalent to treatment status in difference-in-differences setting, while intelligence score of the child is equivalent to time. Therefore, the parallel trends assumption can be translated to Assumption 1.

Assumption 1. Selection bias in parental non-employment status does not vary with

#### intelligence score of child.

Another assumption is that intelligence score of children is not itself an outcome of parental non-employment.

#### Assumption 2. Intelligence score is not determined by parental non-employment.

To put it more formally, denote potential outcome of an individual if exposed to parental non-employment shock as  $y^1$ . Similarly, her potential outcome when parents stay employed is  $y^0$ . The realised outcome is then  $y = y^0 \cdot (1 - UP) + y^1 \cdot UP$ . For simplicity of notation, I omit **X** and **P** from the conditioning set in the following derivations.

The regression coefficient  $\beta_3$  can then be written as

$$\beta_{3} = \frac{\operatorname{Cov}(y_{i}, IQ_{i}|UP_{i} = 1)}{\operatorname{Var}(IQ_{i}|UP_{i} = 1)} - \frac{\operatorname{Cov}(y_{i}, IQ_{i}|UP_{i} = 0)}{\operatorname{Var}(IQ_{i}|UP_{i} = 0)} =$$
(2)  
$$= \beta_{3}^{\star} + \frac{\operatorname{Cov}(y_{i}^{0}, IQ_{i}|UP_{i} = 1)}{\operatorname{Var}(IQ_{i}|UP_{i} = 1)} - \frac{\operatorname{Cov}(y_{i}^{0}, IQ_{i}|UP_{i} = 0)}{\operatorname{Var}(IQ_{i}|UP_{i} = 0)}$$

where  $\beta_3^{\star} = \frac{\operatorname{Cov}(y_i^1 - y_i^0, IQ_i|UP_i = 1)}{\operatorname{Var}(IQ_i|UP_i = 1)}$  is the slope of the causal effect of parental non-employment with respect to intelligence score of the child. The terms  $\frac{\operatorname{Cov}(y_i^0, IQ_i|UP_i)}{\operatorname{Var}(IQ_i|UP_i)}$  capture the selection bias due to parental non-employment being a non-random event. Now, it is easy to see that if the slopes of the selection bias terms with respect to IQ were identical, the two terms would cancel each other out. Hence, the regression coefficient would capture the slope of the causal effect,  $\beta_3 = \beta_3^{\star}$ .

Of course, Assumptions 1 and 2 are strong assumptions and may not hold in the real world. In Section 6 I discuss evidence based on observed characteristics, numerical simulations and sensitivity analysis supporting these assumptions. Nevertheless, both assumptions may still not hold. In that case, the estimate of  $\beta_3$  is descriptive and does not identify causal relationships. I believe that, even then, the results would remain interesting and could be used to motivate future causal analyses on possible ways to mitigate intergenerational losses due to unemployment.

## 5 Results

In this section, I present the results of estimation of Equation (1) in the UKHLS working sample. 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. All regressions are weighted with cross-sectional response weight and standard errors account for the survey design. Finally, I apply multiple inference correction across all outcomes considered in this paper using Benjamini and Hochberg (1995) method controlling the false discovery rate (FDR)<sup>17</sup>.

			Depedent	variables		
	Age left school	Log age left school	Age left educa- tion	Log age left edu- cation	Post-16 school	Degree
Parent nonemp	-0.167***	-0.010***	-0.239*	-0.014**	-0.081***	-0.039***
	(0.029)	(0.002)	(0.131)	(0.006)	(0.014)	(0.013)
IQ	0.301***	$0.018^{***}$	$0.891^{***}$	$0.045^{***}$	$0.138^{***}$	0.131***
	(0.008)	(0.000)	(0.038)	(0.002)	(0.004)	(0.004)
Parent nonemp $\times$ IQ	$-0.066^{\dagger\dagger}$	$-0.004^{\dagger\dagger}$	-0.152	-0.006	$-0.035^{\dagger\dagger}$	$-0.036^{\dagger\dagger\dagger}$
	(0.025)	(0.001)	(0.111)	(0.005)	(0.012)	(0.011)
Obs.	20 293	20 293	20 295	$20 \ 295$	20 307	20 307
Outcome mean	16.62	2.81	19.32	2.94	0.37	0.27
Outcome sd	1.06	0.06	4.67	0.20	0.48	0.44

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

 $^{\dagger}{\rm q}<0.1;\,^{\dagger\dagger}{\rm q}<0.05;\,^{\dagger\dagger\dagger}{\rm q}<0.01$  based on FDR adjusted q-values

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

*Note:* The table reports coefficients from weighted regressions of dependent variables in columns on parental non-employment 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 (Benjamini and Hochberg 1995).

First, I start with the educational outcomes: ages when individuals left school and further education, indicator for staying on at school past the compulsory age 16 (*post-16 school*) and having a degree (*degree*). The results in Table 3 suggest that higher intelligence makes individuals more vulnerable to the losses in education attainment associated with her parents not working. Non-working parents reduce children's years of schooling by 0.8 months for every 1 sd higher intelligence score of children. Compare this effect with 5 months increase in average age left school when minimum school leaving age was raised from 14 to 15 (ROSLA) in 1947 in the UK (Oreopoulos 2006). So, additional losses in years of schooling for every 1 sd higher intelligence score amount to 15% of the ROSLA effect. Besides losses in years of education, these individuals also lag in tertiary degree

<sup>&</sup>lt;sup>17</sup>See Anderson (2008) for a review of various multiple inference corrections. In a nutshell, FDR controls "the expected proportion of rejections that are Type I errors" (Anderson 2008, 16). I apply the correction across all outcomes in main specification, but do separate correction across all outcomes in estimations for robustness checks and heterogeneity.

attainment. For every 1 sd higher intelligence score, probability of having a degree falls by another 3.6 pp. Compare this effect to the 44.8 pp gap in the share of people with degree between 95th and 5th percentiles of the intelligence distribution.

		Depedent	variables	
	Age left	Age left	Post-16	Degree
	school	educa-	school	
		tion		
Parent nonemp $\times$ IQ	0.059	$0.839^{\dagger}$	0.066	0.025
	(0.077)	(0.403)	(0.042)	(0.048)
No school $\times$ Parent nonemp $\times$ IQ	-0.342	-1.154	-0.146	$-0.267^{\dagger\dagger}$
	(0.236)	(1.514)	(0.106)	(0.106)
Some school $\times$ Parent nonemp $\times$ IQ	-0.117	$-0.931^{\dagger}$	$-0.100^{\dagger}$	-0.052
	(0.083)	(0.416)	(0.045)	(0.050)
Qual missing $\times$ Parent nonemp $\times$ IQ	-0.154	$-1.579^{\dagger\dagger\dagger}$	$-0.125^{\dagger\dagger}$	$-0.103^{\dagger}$
	(0.098)	(0.513)	(0.049)	(0.052)
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

 

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

 $^{\dagger}{\rm q}<0.1;\,^{\dagger\dagger}{\rm q}<0.05;\,^{\dagger\dagger\dagger}{\rm q}<0.01$  based on FDR adjusted q-values

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

*Note:* The table reports coefficients from weighted regressions of dependent variables in columns on parental non-employment 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 (Benjamini and Hochberg 1995).

These results show that higher intelligence exacerbates the losses in educational outcomes from non-working parents. That is, instead of protecting children, higher intelligence makes them even more vulnerable. 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 in late childhood are more productive among children with already high level of skills. This implies that high-intelligence teenagers suffer more when their parents reduce human capital investments. 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, in fact, 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<sup>18</sup>, which are likely also children from lower-income families.

	Work	IHS	$\%\Delta$	IHS	$\%\Delta$	Hours
		earnings	earnings	hourly	hourly	
				wage	wage	
Parent nonemp	-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 nonemp $\times$ IQ	$0.048^{\dagger\dagger\dagger}$	$0.126^{\dagger\dagger\dagger}$	$0.130^{\dagger\dagger\dagger}$	$-0.010^{\dagger\dagger}$	$-0.051^{\dagger}$	$1.552^{\dagger\dagger\dagger}$
	(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

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

 $^{\dagger}{\rm q}<0.1;\,^{\dagger\dagger}{\rm q}<0.05;\,^{\dagger\dagger\dagger}{\rm q}<0.01$  based on FDR adjusted q-values

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

*Note:* The table reports coefficients from weighted regressions of dependent variables in columns on parental non-employment indicator and intelligence score. All regressions 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 (Benjamini and Hochberg 1995).

Now, I turn to the labour-market outcomes of children: indicator for working (*work*), real monthly earnings (*IHS earnings*, which I also convert to  $\%\Delta$  earnings following Bellemare and Wichman (2020)), real hourly wages (*IHS hourly wage* and  $\%\Delta$  hourly wage), and usual hours worked per week (*hours*). The results for these outcomes in Table 5 suggest that higher intelligence helps mitigate the cost of parental non-employment. Here, a 1 sd increase in intelligence score improves the effect of parental non-employment on the probability of employment by 4.8 pp and earnings - by 0.13 pp. The table suggests that the positive effect on earnings appear to be driven by higher labour supply on the

<sup>&</sup>lt;sup>18</sup>Parental educational qualifications are self-reported by children and are missing for about a fifth of the sample. I treat missingness as a separate category in the estimations and assume that it is a signal of low educational attainment.

intensive and extensive margins, while there remains a penalty on wages<sup>19</sup>. These results suggest that intelligence does protect individuals in the longer term. Even though higher intelligence made them more susceptible to educational losses, 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 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 non-employment on early career earnings should be flat with respect to intelligence score. Since high-intelligence children with non-working parents are undereducated, they cannot differentiate themselves from other job candidates when first entering the labour market. Second, the rate at which intelligence narrows the gap in outcomes from having non-wokring parents should increase with work experience.

<sup>&</sup>lt;sup>19</sup>In Table G.2 in Online Appendix 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. The results also show the mitigating effect of higher intelligence on earnings and hours worked.

			De	epedent variab	oles		
	Log first job rank	First job manager	First job supervisor	Log current job rank	Log current job rank	Current job manager	Current job supervisor
Parent nonemp	-0.022***	0.006	-0.009	-0.040***	-0.050***	-0.048***	0.003
	(0.007)	(0.008)	(0.015)	(0.012)	(0.017)	(0.015)	(0.014)
IQ	0.007***	0.015***	-0.005	0.083***	0.087***	0.071***	-0.006
	(0.002)	(0.002)	(0.005)	(0.003)	(0.004)	(0.005)	(0.004)
Parent nonemp $\times$ IQ	-0.004	-0.003	-0.024	-0.003	-0.019	-0.018	$0.025^{\dagger}$
	(0.006)	(0.006)	(0.015)	(0.012)	(0.017)	(0.014)	(0.012)
Tenure $> 10$					0.014		
					(0.009)		
Parent nonemp $\times$ Tenure $> 10$					$0.055^{*}$		
					(0.030)		
Parent nonemp × IQ × Tenure > 10					$0.072^{\dagger\dagger}$		
					(0.031)		
Obs.	15 852	17 244	17 244	15 829	11 388	13 810	13 810
Outcome mean	2.51	0.05	0.26	7.70	7.70	0.25	0.14
Outcome sd	0.26	0.22	0.44	0.42	0.42	0.43	0.35

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

 $^{\dagger}{\rm q}<0.1;\,^{\dagger\dagger}{\rm q}<0.05;\,^{\dagger\dagger\dagger}{\rm q}<0.01$  based on FDR adjusted q-values

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

*Note:* The table reports coefficients from weighted regressions of first and current job characteristics on parental non-employment indicator and intelligence score. Both current and first occupations were aggregated to major occupational groups (one-digit SOC) prior to ranking. Ranking is based on real median annual gross earnings of similarly-aged individuals. For more details on ranking procedure see Online Appendix C. Tenure is defined as years since the respondent started the current job. 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 (Benjamini and Hochberg 1995).

To test the first implication I estimate the baseline specification with various characteristics of first and current jobs as the dependent variables<sup>20</sup>. The results are presented in Table 6. Indeed, the effect of parental non-employment on the characteristics of the first jobs does not seem to vary with the intelligence score of children. There is no differential impact on how well paid their first jobs were, nor on the type of roles they performed in those jobs. At first glance, there is also no evidence of intelligence helping to narrow the gap in the ranking of current jobs. The interaction coefficient from the regression of log current job rank is insignificant and close to zero. However, there is a strong positive effect among workers who have been working for their employer for at least 10 years. This is consistent with the prediction of the employer learning theory. The results also indicate differential impact on holding supervisory roles by intelligence score.

In order to test the second implication, I construct a panel dataset of earnings, hours worked and wages by merging information 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 non-employment indicator and intelligence score of individuals. In particular, I estimate the following equation using the fixed-effect regression

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

where  $y_{it}$  is outcome of individual *i* at time *t*,  $F_i$  is female dummy variable,  $\delta_t$  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  $\gamma_{4a}$  is the set of age profiles of interest. It captures the differential impact of parental non-employment 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 Ichino, Rustichini, and Zanella (2024), I use age restrictions informed by the 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 45 and 55). These assumptions imply that earnings profiles are flat between ages 45 and 55. Therefore, I drop the age indicators in this range from the regression equation.

To formulate the null hypothesis, note that the second prediction from the employer-

<sup>&</sup>lt;sup>20</sup>I do not observe earnings at first jobs, except for few cohorts young enough to be observed in the UKHLS at the beginning of their careers. By using the job rankings I proxy earnings of workers with how well-paid their jobs are in general. In addition, the UKHLS includes indicators whether respondents held managerial or supervisory roles in their jobs. This is separate from occupational codes, which explains discrepancies in sample counts.

learning theory can be rewritten as

$$\frac{\partial^2 \mathbb{E}(y^1 - y^0 | UP = 1, IQ, a)}{\partial IQ \; \partial a} \ge 0$$

where a is age.

Let  $a^*$  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

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

Notice that  $\frac{\partial \mathbb{E}(y^1 - y^0 | UP = 1, IQ, a)}{\partial IQ} \equiv \gamma_{4a}$ . Therefore, this condition can be translated to the null hypothesis  $H_0: \gamma_{4,a} \leq 0 \quad \forall a < a^*$  and that  $\gamma_{4a}$  becomes less negative as age increases.

Table 7 reports the estimates of  $\gamma_{4a}$  from fixed-effect regression of Equation (3). Although none of the coefficients attain statistical significance, the point estimates of earnings and wages are consistent with the null hypothesis. The estimates of  $\gamma_{4a}$  are indeed negative at earlier ages and they are increasing with age.

In summary, the results presented in this section suggest that intelligence can shield children from some of the effects of non-working parents, but not all. The impact on educational attainment is exacerbated by higher intelligence, which can be attributed to the dynamic complementarity of human capital investments. As a result, the affected individuals are forced to start their careers at lower-paying jobs. However, as they progress in the labour market, higher intelligence helps them to gradually move to better-paying jobs, be more likely to work and narrow the gap on earnings stemming from having non-working parents. These results are consistent with the prediction of the employer learning theory that ability of workers play larger role in labour-market outcomes of more experienced workers. Note that the present analysis does not include measures of productivity and efficiency, which could also contribute to improvements in earnings besides job characteristics and labour supply.

# 6 Validity

In this section I summarise the evidence in support of Assumptions 1 and 2 necessary for causal interpretation of the main results. For more details, tables and figures refer to the Online Appendix D.

First, I provide direct test of Assumption 1 based on observed pre-determined characteristics at birth in the UKHLS and the BCS70 in the Online Appendix D.1. I use these characteristics as dependent variables in regression Equation (1). While we can expect

		Depedent	variables	
-	Work	IHS earnings	IHS hourly	Hours
			wage	
Ages $16-20$	0.020	-0.433	-0.193	-0.537
	(0.049)	(0.415)	(0.112)	(1.649)
Ages 21-25	0.017	-0.246	-0.110	-0.556
	(0.036)	(0.333)	(0.064)	(1.176)
Ages 26-30	0.018	-0.396	-0.161	-0.588
	(0.025)	(0.277)	(0.063)	(0.864)
Ages 31-35	0.009	-0.282	-0.066	-0.581
	(0.018)	(0.247)	(0.052)	(0.653)
Ages 36-40		-0.252	-0.042	
		(0.219)	(0.045)	
Ages 41-45		0.073	-0.047	
		(0.159)	(0.036)	
Ages 56-60	0.009	0.003	0.011	0.198
	(0.021)	(0.179)	(0.050)	(0.819)
Ages 61-65	0.015	0.077	-0.043	0.812
	(0.036)	(0.271)	(0.070)	(1.280)
Obs.	$175 \ 072$	175 124	134 279	175 124

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

\* p < 0.1, \*\* p < 0.05, \*\*\* p < 0.01 \*<br/>p < 0.1; \*\*p < 0.05; \*\*\*<br/>p < 0.01 based on conventional p-values

Note: The table reports the fixed-effects estimates of the differential impact of parental non-employment 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.

 $\beta_1 \neq 0$  due to selection bias, Assumption 1 implies that  $\beta_3 = 0$ . Indeed, the estimates in both datasets indicate that the selection bias in terms of observed pre-determined characteristics does not vary with intelligence score of children.

Second, I provide numerical analysis in the context of intergenerational transmission of intelligence and its correlation with employment status of parents in the Online Appendix D.2. The idea here is that intelligence of parents, which is unobserved here, can influence both intelligence of children as well as employment probabilities of parents. Due to data limitations<sup>21</sup>, I use simulations under different persistence parameters to show that the Assumption 1 holds when parents' and children's intelligence scores are linearly related<sup>22</sup>.

Third, I examine the sensitivity of the estimated results to unspecified correlation structure of the error terms in the Online Appendix D.3. This exercise addresses the concern that there are other unobserved characteristics of families that can simultaneously determine parental employment status, children's intelligence and other outcomes. I estimate a system of three equations with parental non-employment, intelligence score and earnings of children as outcome variables, fixing the correlations between their error terms at given values. The sensitivity analysis reveals that correlation structure can significantly change estimates of  $\beta_1$  and  $\beta_2$ , but the estimates of  $\beta_3$  are remarkably stable. While this is very encouraging, the results of the sensitivity analysis may change under different distributional assumptions about error terms in the system.

Assumption 2 could be violated if education losses from parental non-employment also translate to lower intelligence of children. However, the intelligence measure I use in this paper is based on performance in general cognitive tasks and is not 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  $10^{23}$ . In case intelligence is, indeed, affected by parental non-employment, I also discuss how the interpretation of  $\beta_3$  would change in the Online Appendix D.4.

# 7 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 the Online Appendix  $\mathbf{F}$ .

First, I examine the robustness to parental non-employment measures in the Online

<sup>&</sup>lt;sup>21</sup>The UKHLS does not provide information on cognitive scores of the respondents' parents.

 $<sup>^{22}</sup>$ 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.

<sup>&</sup>lt;sup>23</sup>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 increase intelligence of children.

Appendix F.1. I begin by comparing the parental non-employment 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 nonemployment 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 non-employment measure.

Another concern is that the parental non-employment indicator does not differentiate between unemployment and long-term non-employment. In the 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.

In the Online Appendix F.3 I replicate the analysis in the BCS70. I use standardised intelligence score constructed from cognitive test results at age 10 and parental non-employment 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 non-employment, 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.

Finally, some readers may be interested in the results by country of birth or ethnicity in the Online Appendix F.4. These estimates are not testing robustness of the results in a strict sense. The reason is that there may be important institutional differences between countries or ethnicities that affect how people respond to parental non-employment. However, one set of results from this exercise is worth highlighting. Since the education system in Scotland has been less selective than in England or Wales (Willetts 2017), educational decisions of people born in Scotland may depend less on parental non-employment in adolescence. Consistent with this, I find that higher intelligence does not exacerbate losses in educational outcomes in Scotland.

# 8 Mechanisms of parental non-employment

The results in this paper suggest that intelligence is both a risk and a protective factor when it comes to how children respond to parents not working. At the beginning, it exacerbates the educational losses. But later in the labour market, higher intelligence helps to bridge the gap in earnings, in part thanks to higher labour supply and having better-paying jobs. The heterogeneous effects on educational outcomes directly relate to the discussion of mechanisms of parental non-employment 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.

	Depende	ent variable: Degree	indicator
-	At birth	Age 10	Age 16
Parent nonemp	0.004	-0.051**	-0.050*
	(0.031)	(0.026)	(0.025)
IQ	0.132***	$0.134^{***}$	$0.135^{***}$
	(0.008)	(0.008)	(0.008)
Parent nonemp $\times$ IQ	-0.030	-0.066**	-0.075***
	(0.029)	(0.028)	(0.027)
Obs.	3 243	3 243	3 243

Table 8: Degree attainment, IQ and parental unemployment across ages in<br/>the BCS70

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

*Note:* The table reports estimation results from main specification with degree attainment as the dependent variable by ages at which parental employment status is measured in the BCS70. Intelligence variable IQ is constructed from the first principal component based on cognitive test results at age 10. Degree indicator is constructed from highest educational qualification at age 26. 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 throughout across all waves used (Mostafa and Wiggins 2014). Standard errors are reported in parentheses.

First, I check the heterogeneity of these effects by age at which employment status of parents is measured in the  $BCS70^{24}$ . 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. If the primary channel is, indeed, loss of human capital investments, then there should be less heterogeneity by intelligence of children when non-employment 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 reports the corresponding estimation results from main specification across ages at which parental non-employment 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.3 in the Online Appendix). Therefore, non-employment of fathers is more likely to result in a substantial reduction of family income. Therefore, the human capital investment channel

 $<sup>^{24}</sup>$ The UKHLS only contains information about a single snapshot of parental statuses at age 14 of the respondents, while the data on children of the UKHLS is not long enough to observe outcomes past age 16.

is likely to operate via father's non-employment rather than mother's non-employment. In Table 9 I report estimation results separately using father's or mother's non-employment indicator. In the bottom panel, I report estimated difference in the interaction effects between the two specifications. The results are in line with the prediction: father's non-employment status appears to be more relevant in explaining the heterogeneity by intelligence of children. Nevertheless, these results are also consistent with the mental distress channel as argued by Rege, Telle, and Votruba (2011).

	Dependent variables							
	Degree	Work	$\%\Delta \text{ earnings}$	$\%\Delta$ hourly				
				wage				
Panel A: Mother's non-emple	oyment							
Mother nonemp	0.007	-0.040***	-0.190***	-0.020				
	(0.007)	(0.007)	(0.026)	(0.018)				
IQ	0.129***	0.049***	0.290***	$0.156^{***}$				
	(0.004)	(0.005)	(0.016)	(0.010)				
Mother nonemp $\times$ IQ	-0.003	$0.024^{\dagger\dagger}$	$0.054^{\dagger}$	0.005				
	(0.007)	(0.008)	(0.026)	(0.018)				
Obs.	19  984	19  984	19  984	15  394				
Panel B: Father's non-emplo	yment							
Father nonemp	-0.035**	-0.064***	-0.293***	-0.129***				
	(0.015)	(0.016)	(0.052)	(0.025)				
IQ	0.133***	$0.051^{***}$	0.291***	$0.161^{***}$				
	(0.004)	(0.004)	(0.014)	(0.009)				
Father nonemp $\times$ IQ	$-0.033^{\dagger\dagger}$	$0.045^{\dagger\dagger}$	$0.107^{\dagger}$	$-0.075^{\dagger\dagger}$				
	(0.013)	(0.016)	(0.050)	(0.028)				
Obs.	18 819	18 819	18 819	14  630				
Panel C: Parent difference								
	$-0.030^{\dagger}$	0.021	0.051	$-0.014^{\dagger\dagger}$				
	(0.014)	(0.017)	(0.056)	(0.005)				

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

 $^{\dagger}{\rm q}<0.1;\,^{\dagger\dagger}{\rm q}<0.05;\,^{\dagger\dagger\dagger}{\rm q}<0.01$  based on FDR adjusted q-values

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

*Note:* The table reports coefficients from weighted regressions of dependent variables in columns on father's and mother's non-employment indicators and intelligence score. 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 (Benjamini and Hochberg 1995).

Finally, I also examine the heterogeneity of the results by gender of children in Table 10. The point estimates are largely similar to the main results. None of the coefficients are statistically significant after correction for multiple inference. However, the estimates for degree and wages among men are significant at 5% and 10% when using conventional p-values. There appear to be no differences in the responses of women: although point estimates for labour-market outcomes are positive, they are indistinguishable from zero both before and after correction for multiple inference.

		Dependen	t variables	
	Degree	Work	$\%\Delta$	$\%\Delta$ hourly
			earnings	wage
Parent nonemp	-0.033*	-0.045**	-0.270***	-0.135***
	(0.020)	(0.019)	(0.067)	(0.031)
IQ	$0.131^{***}$	$0.052^{***}$	0.299***	$0.172^{***}$
	(0.005)	(0.006)	(0.021)	(0.009)
Parent nonemp $\times$ Female	-0.010	-0.028	-0.016	0.041
	(0.024)	(0.027)	(0.091)	(0.053)
$IQ \times Female$	0.000	0.000	-0.006	-0.023
	(0.006)	(0.008)	(0.026)	(0.018)
Parent nonemp $\times$ IQ	-0.034	0.027	0.080	-0.066
	(0.017)	(0.020)	(0.067)	(0.034)
Parent nonemp $\times$ IQ $\times$ Female	-0.004	0.037	0.093	0.032
	(0.021)	(0.026)	(0.086)	(0.051)
Obs.	20 307	20 307	20 307	$15 \ 643$

Table	10:	Effect	of	parental	unem	olo	yment	by	gender	and	intelli	gence	score
								· •/	<b>O C C C C</b>			<b>n</b>	

 $^{\dagger}q<0.1;\,^{\dagger\dagger}q<0.05;\,^{\dagger\dagger\dagger}q<0.01$  based on FDR adjusted q-values  $^{*}p<0.1;\,^{**}p<0.05;\,^{***}p<0.01$  based on conventional p-values

*Note:* The table reports coefficients from weighted regressions of dependent variables in columns on parental non-employment 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 (Benjamini and Hochberg 1995).

#### Conclusion 9

The topic of how parental job loss affects children has been receiving 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 interacts with parental non-employment

in determining outcomes of children. Using the UK survey data, 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.

I find that, 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. To support this interpretation, I show that most of the damaging effect of high intelligence is concentrated among children with less-educated parents - they are more likely to have experienced losses in human capital investments.

Nevertheless, later in the labour market higher intelligence helps them to narrow the gap in earnings. In part, this can be explained by higher labour supply. I also show that higher intelligence helps children of non-working parents to get generally better-paying jobs. These results are consistent with the employer learning theory. I show that the impact of parental non-employment on occupation rank of first jobs does not vary with intelligence. Thus, losses in education among high-intelligence children forces them to start 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. The labour market analysis in this paper does not consider other margins of response, such as productivity, that could also be important factors.

These findings demonstrate that higher intelligence helps children to overcome some of the effects of parental unemployment experienced during adolescence. Furthermore, the results are consistent with the losses in human capital investments into children as the leading channel through which non-working parents affect 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 employment is measured. This is again consistent with the dynamic complementarity theory. I also show that the main findings operate through father's employment status, which can also support the income channel interpretation since fathers were traditionally primary earners in the family.

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