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Does intelligence shield children from the effects of parental non-employment?☆

Nurfatima Jandarova

Centre of Excellence in Tax Systems Research, Tampere University at Kanslerinrinne 1, 33014 Tampereen yliopisto, Finland

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ABSTRACT

Current literature offers several potential channels through which jobless parents 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 gap in education widens with higher intelligence, while the gap in labour-market outcomes narrows. I rationalise these findings using the skill formation and employer learning theories.

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 labour-market outcomes of children. These effects are especially pronounced among children from disadvantaged backgrounds.[1] Various papers propose different channels through which parental unemployment affects children. In this paper, I present new evidence based on how intelligence of children can change the intergenerational effects of jobless parents.

Studying the heterogeneity across intelligence distribution can improve our understanding of channels through which parental joblessness acts on children. On the one hand, higher cognitive skills can help increase resilience in the face of negative shocks throughout childhood (Masten et al., 1999). For example, if having non-working parents during teenage years affects children mainly through stress and worse family interactions, then higher intelligence can mitigate these 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[2] 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

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E-mail address: nurfatima.jandarova@tuni.fi.

[1] Oreopoulos, Page, and Stevens (2008) and 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.

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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 focuses on the interaction of parental employment status and children's intelligence score. Since parental employment status available in the data does not allow me to isolate exogenous job losses, I cannot study the causal effect of parental unemployment directly. Nevertheless, I argue that the coefficient of the interaction term can have a causal interpretation under two assumptions. First, the selection bias in terms of outcomes of children with working and non-working parents does not vary with their intelligence. Second, intelligence of children is not itself an outcome of parental non-employment. Under these assumptions, I can study the slope of the causal effect of parental non-employment with respect to intelligence of children. I discuss and provide 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, higher intelligence widens the gap in educational outcomes due to non-working 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 in the labour market, on the contrary, higher intelligence helps to bridge the gap in children's 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.[3]

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[4], 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 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 show additional heterogeneity 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 of parental non-employment and intelligence of children becomes more negative with age at which parental non-employment occurs. 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 family income and, likely, larger losses in human capital investments. I find that the 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[5] and small or zero effects on labour market outcomes of children.[6] Such variation can be related to institutional differences between countries in which the question has been studied (Lindemann & 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 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 (2024) study the academic achievements

[3] 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.

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

[5] Brand and Thomas (2014), Bratberg, Nilsen, and Vaage (2008), Coelli (2011), Page et al. (2009), Pan and Ost (2014), Peter (2016), Rege, Telle, and Votruba (2011) and Stevens and Schaller (2011).

[6] Bratberg et al. (2008), Hilger (2016), Mörk, Sjögren, and Svaleryd (2019) and Page et al. (2009).

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 (Brand & Thomas, 2014; Coelli, 2011; Di Maio & Nisticò, 2019; Oreopoulos et al., 2008; Page et al., 2009; Pan & Ost, 2014; Rege et al., 2011). At the same time, the institutional environment can moderate the intensity of these effects (Lindemann & 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 job loss 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 either mitigate or exacerbate the effects of parental unemployment.

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 (Fig. 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? 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 (Akee, Copeland, Keeler, Angold, & Costello, 2010; Brand & Thomas, 2014; Rege et al., 2011; Stevens & Schaller, 2011). 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 psychology literature, Gale, Hatch, Batty, and Deary (2009) and Masten et al. (1999) find that cognitive skills help children overcome 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 & 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, Pekrun, Suzuki, Marsh, & Lichtenfeld, 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),[8] 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.[9]

I restrict the analysis sample to individuals who (i) had non-zero response weight[10] (42 964), (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

[7] See, for example, Chevalier, Harmon, O'Sullivan, and Walker (2005) and Dearden, McGranahan, and Sianesi (2004) for the discussion of the importance of credit constraints for educational choices in the UK.

[8] University of Essex, Institute for Social and Economic Research (2020).

[9] 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.

[10] 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.

[11] 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.

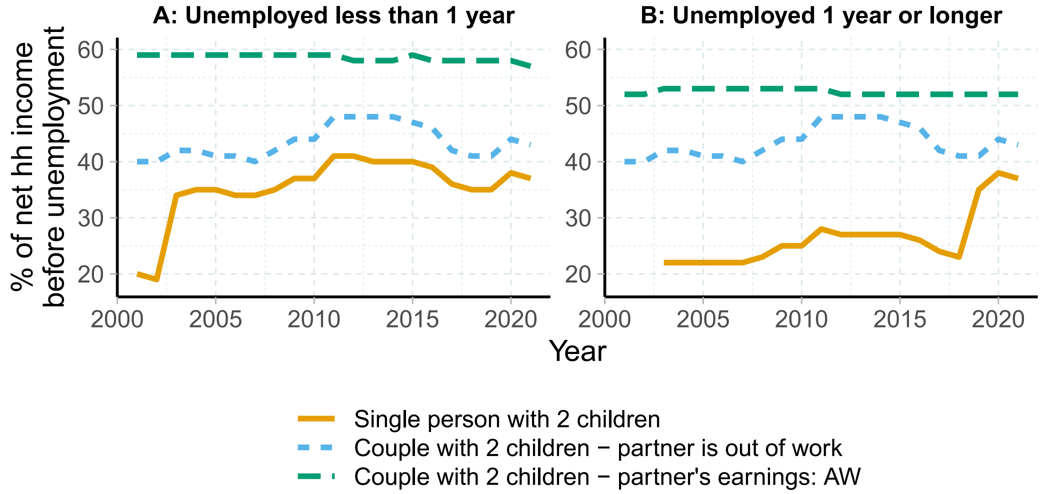

Fig. 1. Net replacement rate of income during unemployment.
Note: The plots display net replacement rates of household income during unemployment in the UK as a share of previous in-work income by types of households and duration of unemployment.
Source: The data source is OECD (2023).

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 account for attrition. For a more detailed description of the dataset, working sample and variables see the 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 one if they were not working, zero if they were working and missing otherwise.[13] 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.[14] The final parental non-employment indicator has 901 missing observations. Table G.2 in the Online Appendix 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. Using auxiliary data on employment in years when most of the analysis sample was 14 years old, Figure G.2 in the Online Appendix shows that 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. Table 1 also shows that individuals whose parents were not working are significantly different from those whose parents were working. 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.

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

[12] Chamberlain and University of London, Institute of Education, Centre for Longitudinal Studies, and Chamberlain (2013).
[13] 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.
[14] At the time when the respondents in the analysis sample were growing up, fathers were predominantly primary earners in the household (Figure G.1 in the Online Appendix).

Table 1
UKHLS descriptive statistics by parental employment status.

Variable	Working parents			Non-employed parents			Diff	SE
	Mean	SD	N	Mean	SD	N		
Age	41.408	12.247	18 569	37.137	12.537	1738	−4.27†††	0.401
Female	0.511	0.500	18 569	0.538	0.499	1738	0.027†	0.015
British	0.946	0.225	18 511	0.882	0.322	1719	−0.064†††	0.008
Parents w/ degree	0.148	0.356	15 722	0.099	0.299	1357	−0.049†††	0.012
School-leaving age	16.597	1.069	18 564	16.331	0.901	1738	−0.266†††	0.027
Post-16 school	0.374	0.484	18 569	0.225	0.418	1738	−0.149†††	0.013
Degree	0.286	0.452	18 569	0.174	0.379	1738	−0.112†††	0.011
IQ score	0.028	0.993	18 569	−0.337	1.022	1738	−0.365†††	0.031
Work	0.770	0.421	18 569	0.633	0.482	1738	−0.137†††	0.014
Self empl	0.098	0.297	18 569	0.063	0.243	1738	−0.035†††	0.008
IHS earnings	2.752	1.605	18 569	2.159	1.678	1738	−0.593†††	0.050
Earn > 0	0.792	0.406	18 569	0.667	0.472	1738	−0.125†††	0.014
Earn > med	0.525	0.499	18 569	0.390	0.488	1738	−0.135†††	0.016
Log current job rank	7.724	0.406	14 684	7.601	0.428	1145	−0.124†††	0.016
Log first job rank	2.505	0.263	14 695	2.519	0.271	1157	0.014	0.010

†q < 0.1; ††q < 0.05; †††q < 0.01 based on FDR adjusted q-values.
Note: The table reports descriptive statistics in the working dataset by parental employment status. For the definition of analysis sample, see Section 3. The first three columns of the table report statistics for the subsample with working parents, the next three — for the subsample with non-employed parents. The last two columns show estimated differences in means with standard errors. The estimates are weighted by the response probabilities and standard errors are clustered at the sampling unit level. 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 & Hochberg, 1995).

Table 2
Average outcomes by intelligence score.

	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

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.

effects, prior to running the PCA I standardise the test results within each birth cohort group, defined by five-year windows of year of birth, and gender. I also normalised 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.

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 a respondent has 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 the 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.[15]

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, Fumagalli, Buck, & Avram, 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 $\text{arcsinh}(x) = \ln(x + \sqrt{x^2 + 1})$, which allows

[15] 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.

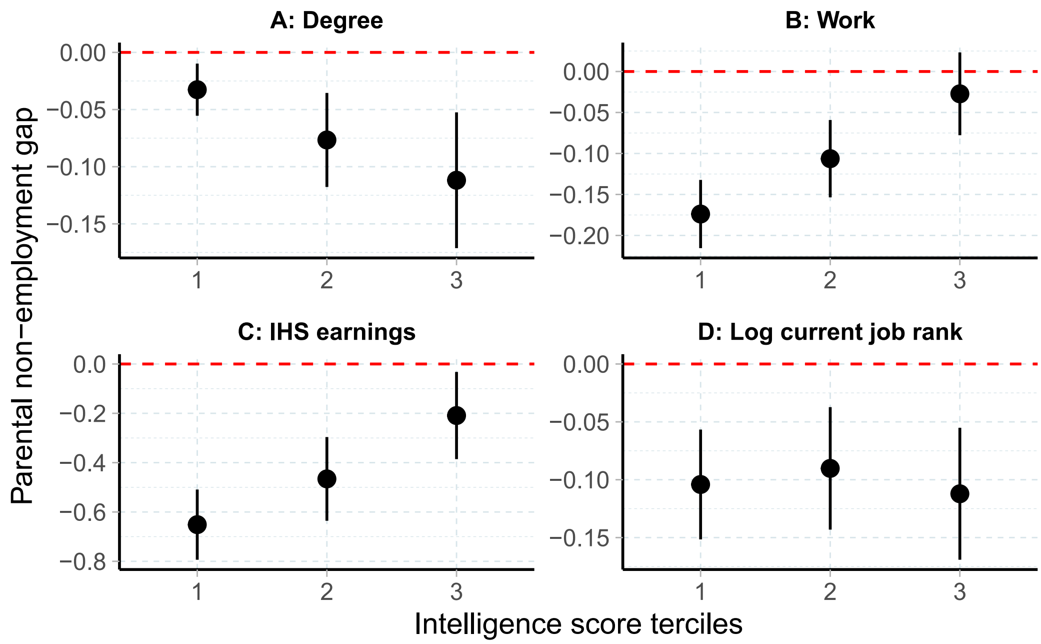

Fig. 2. Average gap in outcomes due to parental non-employment by intelligence terciles.
Note: The figure plots parental non-employment gaps in outcome variables in each panel by terciles of intelligence score. Parental non-employment gap is computed as the difference in sample mean among individuals with non-working parents relative to those with working parents at age 14.

zero and negative values of transformed variable. For large values of x, the coefficients from a regression of $\mathrm{arcsinh}(x)$ 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.[16] 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 and move to higher paying jobs over time.

3.5. Descriptive evidence

Before turning to the estimation strategy and results, I examine graphical evidence. Fig. 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 gap associated with parental non-employment: the average outcomes are typically lower among children with non-working parents. 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 et al., 2008). Second, the gap varies with intelligence 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.

[16] 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.

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

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

where y_i is outcome of individual i, UP_i is the indicator if a parent was 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, β_1 captures the gap in outcomes of children with non-employed 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 (Hilger, 2016; Pan & Ost, 2014), use propensity score matching (Mörk et al., 2019; Peter, 2016), focus on plausibly exogenous job loss events (Oreopoulos et al., 2008; Rege et al., 2011; Stevens & Schaller, 2011) or control for sufficiently long history prior to unemployment (Oreopoulos et al., 2008; Rege et al., 2011). Unfortunately, the UKHLS provides limited information about parents of the respondents that is not sufficient for either of these strategies.

Even though parental non-employment effect cannot be estimated causally by β_1 in Eq. (1), I argue that the interaction coefficient β_3 can have a causal interpretation under two assumptions: Assumptions 1 and 2.

Assumption 1. Selection bias in outcomes of children by parental employment status does not vary with intelligence score of child.

Here, the selection bias refers to the relationship between parental employment status and children's hypothetical outcomes in the case where their parents would have been working. See Eq. (2) for a mathematical formulation of the selection bias.[17]

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 $\mathbf{X}$ and $\mathbf{P}$ from the conditioning set in the following derivations.

The regression coefficient β_3 can then be written as

$$\beta_3 = \frac{\text{Cov}(y_i, IQ_i|UP_i = 1)}{\text{Var}(IQ_i|UP_i = 1)} - \frac{\text{Cov}(y_i, IQ_i|UP_i = 0)}{\text{Var}(IQ_i|UP_i = 0)} \tag{2}$$

$$= \beta_3^\star + \underbrace{\frac{\text{Cov}(y_i^0, IQ_i|UP_i = 1)}{\text{Var}(IQ_i|UP_i = 1)} - \frac{\text{Cov}(y_i^0, IQ_i|UP_i = 0)}{\text{Var}(IQ_i|UP_i = 0)}}_{\text{Selection bias}}$$

where $\beta_3^\star = \frac{\text{Cov}(y_i^1 - y_i^0, IQ_i|UP_i=1)}{\text{Var}(IQ_i|UP_i=1)}$ is the slope of the causal effect of parental non-employment with respect to intelligence score of the child. The terms $\frac{\text{Cov}(y_i^0, IQ_i|UP_i)}{\text{Var}(IQ_i|UP_i)}$ capture the selection bias due to parental non-employment being a non-random event and can be interpreted as the slope of expected outcome $\mathbb{E}\left(y_i^0|IQ_i, UP_i\right)$ with respect to intelligence. Now, it is easy to see that if the slopes of the selection bias terms 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 practice. In Section 6 I discuss the validity of these assumptions and provide some evidence supporting them. Nevertheless, if they are violated, the estimate of β_3 is descriptive and does not identify causal relationships. I believe that the results would remain interesting and could be used to motivate future causal analyses.

5. Results

In this section, I present the results of estimation of Eq. (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).[18]

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 are presented in Table 3. The baseline correlations of the outcomes with parental non-employment and intelligence are as expected. Having a non-working parent is associated with lower academic achievement, while intelligence score generally improves education outcomes. The interaction coefficient, however, shows that losses associated with parental non-employment widen with intelligence. Non-working parents reduce children's years of schooling by 0.8 months more 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 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.

These results show that higher intelligence exacerbates the losses in educational outcomes from having non-working parents. Though surprising, the result is consistent with the literature on human capital investments and skill formation. According to the theory of dynamic complementarity of skills (Cunha & Heckman, 2007), human capital investments in late childhood are more productive among children with already high level of skills. This implies that the gap between teenagers that receive and do not receive human capital investments widens with their intelligence. The negative interaction estimates in Table 3 are in line with this prediction. To fully support the implication of the dynamic complementarity theory, I would also need to show that children at the higher end of the ability distribution do, in fact, lose human capital investments when their parents are not working. Unfortunately, the data does not allow me to verify this statement directly. Instead, I rely on the theory of intergenerational transmission of earnings (Becker & 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 negative effect of the interaction between parental non-employment and children's intelligence score is primarily observed among children with less educated parents,[19] which are likely also children from lower-income families.

Next, 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 & Wichman, 2020), real hourly wages (*IHS hourly wage* and *%Δ hourly wage*), and usual hours worked per week (*hours*). The results for these outcomes are presented in Table 5. Again, the baseline associations are as expected: a non-working parent is associated with worse labour market outcomes, while higher intelligence score — with better outcomes. But now, contrary to the results for educational outcomes, the interaction between parental non-employment and intelligence has a positive effect on labour supply and earnings. Here, a 1 sd increase in intelligence score narrows the gap from parental non-employment on the probability of children's employment by 4.8 pp and earnings — by 0.13 pp. Despite this, the interaction has negative effect on the hourly wages, i.e., higher intelligence widens the gap in wages.[20] Overall, these results suggest that higher intelligence mitigates potentially negative effect of non-working parents in the longer term.

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,

[17] Under the assumption of linear conditional expectation function (CEF), the selection bias term can be interpreted as the difference in slope of the CEF with respect to intelligence score by parental status: $\frac{\partial \mathbb{E}(y_i^0|IQ_i, UP_i=1)}{\partial IQ_i} - \frac{\mathbb{E}(y_i^0|IQ_i, UP_i=0)}{\partial IQ_i}$. In other words, CEFs of potential outcomes are parallel with respect to intelligence score of children between groups of children with non-employed and working parents.

[18] 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.

[19] Parental educational qualifications are self-reported by children and are missing for about a fifth of the sample. I treat missing qualifications as a separate category in the estimations and interpret it as a signal of low educational attainment.

[20] In Table G.3 in the 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.

Table 3
Education of children by parental non-employment and intelligence.

	Dependent variables					
	Age left school	Log age left school	Age left education	Log age left education	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 × IQ	−0.066††	−0.004††	−0.152	−0.006	−0.035††	−0.036†††
	(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

†q < 0.1; ††q < 0.05; †††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 & Hochberg, 1995).

Table 4
Education of children by parental non-employment, intelligence and parental qualifications.

	Dependent variables			
	Age left school	Age left education	Post-16 school	Degree
Parent nonemp × IQ	0.059	0.839†	0.066	0.025
	(0.077)	(0.403)	(0.042)	(0.048)
No school × Parent nonemp × IQ	−0.342	−1.154	−0.146	−0.267††
	(0.236)	(1.514)	(0.106)	(0.106)
Some school × Parent nonemp × IQ	−0.117	−0.931†	−0.100†	−0.052
	(0.083)	(0.416)	(0.045)	(0.050)
Qual missing × Parent nonemp × IQ	−0.154	−1.579†††	−0.125††	−0.103†
	(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

†q < 0.1; ††q < 0.05; †††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 & Hochberg, 1995).

Table 5
Labour market outcomes of children by parental non-employment and intelligence.

	Dependent variables					
	Work	IHS earnings	%Δ earnings	IHS hourly wage	%Δ hourly wage	Hours
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 × 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 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 & Hochberg, 1995).

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 (Altonji & Pierret, 2001; Arcidiacono et al., 2010; Farber & Gibbons, 1996). When workers can send additional signals about their productivity after entering the labour market, the educational signal becomes less important in wage setting over time 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 wider gap in educational achievements due to parental non-employment, 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

Table 6
Job rankings of children by parental non-employment and intelligence.

	Dependent variables						
	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 × IQ	−0.004	−0.003	−0.024	−0.003	−0.019	−0.018	0.025†
	(0.006)	(0.006)	(0.015)	(0.012)	(0.017)	(0.014)	(0.012)
Tenure > 10					0.014		
					(0.009)		
Parent nonemp × Tenure > 10					0.055*		
					(0.030)		
Parent nonemp × IQ × Tenure > 10					0.072††		
					(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

†q < 0.1; ††q < 0.05; †††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 the 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 & Hochberg, 1995).

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 higher intelligence narrows the gap in labour-market outcomes associated with non-working parents should increase with work experience.

To test the first implication I estimate the baseline specification with various characteristics of first and current jobs as the dependent variables. Higher job rankings are associated with better-paying occupations.[21] In addition to occupation codes, the dataset also has indicators for managerial/supervisory roles within jobs.[22] 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

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

where y_{it} is outcome of individual i at time t, F_i is female dummy variable, δ_t and c_i are time and individual fixed effects, respectively. The coefficient γ_{1a} captures the baseline age profile (among men with working parents and mean intelligence score) and $\gamma_{2a}, \gamma_{3a}, \gamma_{4a}, \gamma_{5a}$ represent change in slope of the age profile associated with the corresponding covariates. γ_{4a} is the coefficient of interest which shows 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 35 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-learning theory can be rewritten as

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

where a is age.

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

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

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 $H_0 : \gamma_{4,a} \leq 0 \quad \forall a < a^\star$ and that γ_{4a} becomes less negative as age increases.

Table 7 reports the estimates of γ_{4a} from fixed-effect regression of Eq. (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 γ_{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 both exacerbate and mitigate the losses associated with non-working parents. The gap in educational attainment widens with higher intelligence, which can be attributed to the dynamic complementarity of human capital investments. However, as they gain more labour market experience, higher intelligence helps narrow the gaps

[21] I do not observe earnings at first jobs directly, except for few cohorts young enough to be observed in the UKHLS at the beginning of their careers. But the data has occupation codes of the first jobs for most of the adult sample. I rank these occupations by median earnings of young workers in the UK population. For comparability, I construct similar median-earnings based rankings for current jobs. For more details, see the Online Appendix C.

[22] This is a separate question from occupational codes, which explains the discrepancies in sample counts.

Table 7
Labour market outcomes of children by parental non-employment and intelligence over the lifecycle.

	Dependent variables			
	Work	IHS earnings	IHS hourly wage	Hours
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

*p < 0.1; **p < 0.05; ***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.

in earnings. These results are consistent with the prediction of the employer learning theory that the ability of workers plays 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 1 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.

I begin with the discussion of Assumption 1. This assumption requires that the difference in average outcomes of children by parental status does not vary with children's intelligence score. It is a strong assumption and may be violated in real life. For example, the literature on employment of parents of children with learning disabilities has demonstrated lower working hours, lower earnings and higher probability of non-employment (Saunders et al., 2015; Shearn, 1998; Towers, 2009). Although documented to a lesser extent, parents of gifted children may also face unique challenges in caregiving and child-rearing that could potentially influence their labour supply decisions (Colangelo & Dietmann, 1983; Wood & Peterson, 2017). It might be reasonable to assume that such children would perform worse had their parents been working and, therefore, provide less care or assistance. However, such cases are likely to occur in tails of the intelligence distribution, typically two standard deviations below or above the mean (Maulik, Mascarenhas, Mathers, Dua, & Saxena, 2011; Wood & Peterson, 2017). Using the causal notation from Section 4, a plausible situation could be described by $\mathbb{E}(y_i^0|UP_i = 1, IQ_i) - \mathbb{E}(y_i^0|UP_i = 0, IQ_i)$ increasing (decreasing) in IQ_i at the bottom (top) of the intelligence distribution. Then, the results in this paper would underestimate the slope of the gap at the bottom and overestimate it at the top of intelligence distribution (see the Online Appendix D.1 for graphical illustration). It is worth noting that in the context of regression Eq. (1) it is sufficient for the Assumption 1 to be valid around the mean of intelligence distribution.[23] Below I present the results of a few tests that offer support to this assumption.

[23] I standardise the intelligence score used in estimations to zero mean and unit variance.

First, I provide a direct test of Assumption 1 based on observed pre-determined characteristics at birth in the UKHLS and the BCS70 in the Online Appendix D.2. I use these characteristics as dependent variables in the regression Eq. (1). Even though these characteristics are fixed at birth and do not causally depend on parental employment status 14 years later, there may still be differences in average outcomes of children of non-employed and employed parents due to selection bias. Therefore, I expect $\beta_1 \neq 0$ in these regressions. Crucially, if Assumption 1 holds, then the selection bias does not vary with intelligence of children, implying $H_0 : \beta_3 = 0$. Indeed, the estimates in both datasets fail to reject the null hypothesis. It is possible that Assumption 1 holds, at least at the mean of intelligence distribution.

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.3. 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,[24] I use simulations under different persistence parameters to show that the Assumption 1 holds when parents' and children's intelligence scores are linearly related.[25]

Third, I examine the sensitivity of the estimated results to unspecified correlation structure of the error terms in the Online Appendix D.4. 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 β_1 and β_2, but the estimates of β_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.

[24] The UKHLS does not provide information on cognitive scores of the respondents' parents.

[25] 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.

Table 8
Degree attainment of children by parental non-employment and intelligence across ages in the BCS70.

	Dependent 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 × IQ	−0.030	−0.066**	−0.075***
	(0.029)	(0.028)	(0.027)
Obs.	3243	3243	3243

*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 & Wiggins, 2014). Standard errors are reported in parentheses.

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.[26] In case intelligence is, indeed, affected by parental non-employment, I also discuss how the interpretation of β_3 would change in the Online Appendix D.5.

7. Robustness

In this Section 1 provide a brief summary of checks showing the results are robust to alternative specifications and sample choices. Detailed descriptions and the results are presented in the Online Appendix F.

First, I examine the robustness to parental non-employment measures in the Online 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 similar in the sample of cohorts with low discrepancy between non-employment measure and 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 the gap in educational outcomes due to non-working parents widens with higher intelligence of children, while the gaps in labour market outcomes narrow with intelligence. In particular, the 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 losses in human capital investments are driving the effects. In this Section 1 provide additional 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.[27] 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 this 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 is likely to be stronger with non-working fathers compared to non-working mothers. 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. However, these results are also consistent with the mental distress channel as argued by Rege et al. (2011).

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

[27] 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 respondents is not long enough to observe their outcomes past age 16.

Table 9
Outcomes of children by parental non-employment, intelligence and parent gender.

	Dependent variables			
	Degree	Work	%Δ earnings	%Δ hourly wage
Panel A: Mother's non-employment				
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 × IQ	−0.003	0.024††	0.054†	0.005
	(0.007)	(0.008)	(0.026)	(0.018)
Obs.	19 984	19 984	19 984	15 394
Panel B: Father's non-employment				
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 × IQ	−0.033††	0.045††	0.107†	−0.075††
	(0.013)	(0.016)	(0.050)	(0.028)
Obs.	18 819	18 819	18 819	14 630
Panel C: Parent difference				
	−0.030†	0.021	0.051	−0.014††
	(0.014)	(0.017)	(0.056)	(0.005)

†q < 0.1; ††q < 0.05; †††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 & Hochberg, 1995).

Table 10
Outcomes of children by parental non-employment, intelligence and child gender.

	Dependent variables			
	Degree	Work	%Δ earnings	%Δ hourly 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 × Female	−0.010	−0.028	−0.016	0.041
	(0.024)	(0.027)	(0.091)	(0.053)
IQ × Female	0.000	0.000	−0.006	−0.023
	(0.006)	(0.008)	(0.026)	(0.018)
Parent nonemp × IQ	−0.034	0.027	0.080	−0.066
	(0.017)	(0.020)	(0.067)	(0.034)
Parent nonemp × IQ × 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

†q < 0.1; ††q < 0.05; †††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 & 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.

9. Conclusion

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. Using the UK survey data, I provide new evidence on how intelligence of children interacts with parental non-employment in determining outcomes of children. By exploiting the variation with intelligence, I also contribute to the ongoing discussion about mechanisms through which parental unemployment impacts children.

I find that, initially, higher intelligence widens the gap from non-working parents in educational attainment of children. This finding is consistent with the dynamic complementarity theory (Cunha & Heckman, 2007), which predicts that loss of human capital investments affects high-skill adolescents more. To support this interpretation, I show that most of the negative interaction effect from parental non-employment and children's intelligence is concentrated among children of less-educated parents — they are more likely to have experienced losses in human capital investments.

Nevertheless, later in the labour market higher intelligence helps 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. 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 non-employment 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 widening education gap with intelligence of children is more pronounced when parental non-employment occurs in late childhood and adolescence. This is again consistent with the dynamic complementarity theory of human capital investments. 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.

Appendix A. Supplementary data

Supplementary material related to this article can be found online at https://doi.org/10.1016/j.econedurev.2024.102620.

Data availability

The authors do not have permission to share data.

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