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

Online Appendices

(Not meant to be part of the journal publication)

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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 labour-market outcomes. I rationalise these findings using the skill formation and employer learning theories.

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Appendix A Education system in the UK

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

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

Typically, the way students can demonstrate such knowledge is via GCE A-level grades. The A-level exams are subject-specific and students usually sit three or four of them at the age of 18. In principle, students are free to choose any combination of subjects; in reality, the choices are shaped by the entry requirements of the programs they wish to apply to. Students usually study the subjects in-depth for two years before taking the exam[1]. The admission to the programs that prepare for A-level exams often require good grades in GCSE (General Certificate of Secondary Education)[2] exams taken at the end of compulsory school at age 16. Similar to A-level exams, GCSEs are also subject-based examinations for which students study in the last two-three years of secondary school. Students usually sit at least five GCSE exams in subjects of their choice. Universities may also take into account GCSE grades when making admission decisions.

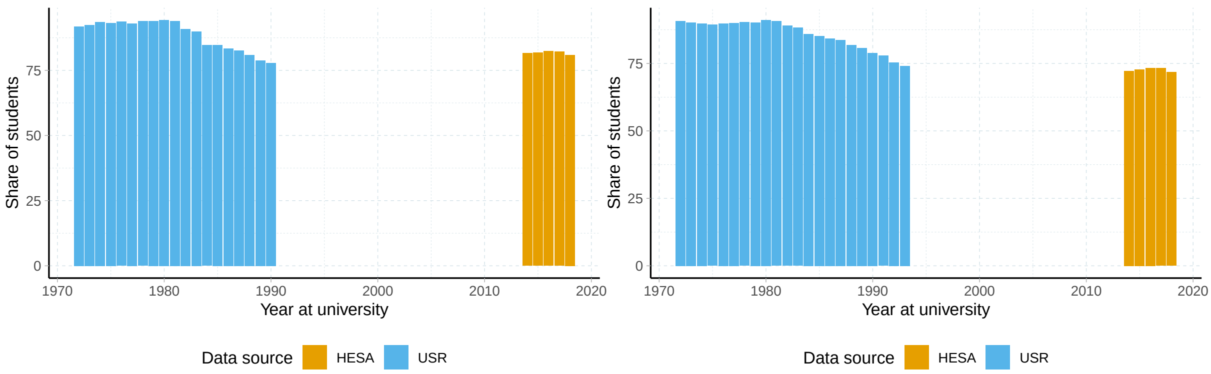
Scotland has its own system of school-leaving qualifications. For most of my analysis sample the relevant qualification is Scottish Certificate of Education (SCE) that was in place during 1962-1999. The SCE had two grades: Ordinary (later Standard) and Higher, which are broadly equivalent to GCSE and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

The data confirms that majority of university students enter via main route: passing three or more A-level exams in the specified subjects. Figure A.1 demonstrates that about

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

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

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



(a) **GCE/SCE as main entry qualification**

(b) **New entrants under age 20**

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

Figure A.1: Characteristics of new university entrants

80-90% of all first-time undergraduate students had GCE and/or SCE exam passes as the main entry qualification and were under age 20. Therefore, the suggested timeline of first passing GCSE exams at 16 and GCE A-level exams at 18 is relevant for most of the children considering a university education.

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

Table B.1: BCS70 sample size across waves

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

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

Appendix B British Cohort Study 1970

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

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

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

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

[4] Chamberlain, University of London, Institute of Education, Centre for Longitudinal Studies, and Chamberlain (1970 British Cohort Study: Birth and 22-Month Subsample, 1970-1972)

[5] Butler et al. (1970 British Cohort Study: Five-Year Follow-Up, 1975)

[6] Butler et al. (1970 British Cohort Study: Five-Year Follow-Up, 1975)

[7] Bynner, University of London, Institute of Education, Centre for Longitudinal Studies, and Butler (1970 British Cohort Study: Sixteen-Year Follow-Up, 1986)

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

takes place by age 10 (Hopkins and Bracht 1975; Cunha and Heckman 2007), I use the intelligence score at age 10 as the main indicator of intelligence of BCS70 cohort members. Out of 13,775 original cohort members observed at age 10, intelligence score is missing for 2,223 individuals. Table B.2 shows that, at least in terms of characteristics at birth, the subsamples with missing and non-missing intelligence scores are nearly identical.

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

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

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

	Full sample			No IQ score			Has IQ score		
Variable	Mean	SD	N	Mean	SD	N	Mean	SD	N
Female	0.481	0.5	13775	0.472	0.499	2223	0.482	0.5	11552
Birthweight, g	3 314.3	526.5	13763	3 283.6	513.4	2221	3 320.1	528.7	11542
Parity	1.234	1.404	13758	1.287	1.525	2215	1.225	1.379	11543
Height of mother, cm	161.1	6.4	13646	161.2	6.4	2195	161	6.4	11451
Mother married	0.977	0.151	13761	0.975	0.157	2221	0.977	0.15	11540
Age of mother	26.175	5.44	13757	26.34	5.585	2220	26.143	5.411	11537
Age of father	29.015	6.412	11085	29.336	6.693	1749	28.955	6.357	9336
Age mother left edu	15.653	1.989	13672	15.671	2.241	2206	15.649	1.938	11466
Age father left edu	16.021	3.674	13185	16.174	4.512	2108	15.991	3.491	11077
Mother unemp at birth	0.946	0.226	9862	0.945	0.228	1581	0.946	0.225	8281
Father unemp at birth	0.031	0.173	12860	0.034	0.181	2064	0.03	0.171	10796
Parents unemp at age 16	0.087	0.282	6366	0.097	0.297	948	0.085	0.279	5418

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

Table B.3: **BCS70 descriptive statistics and missing parental non-employment**

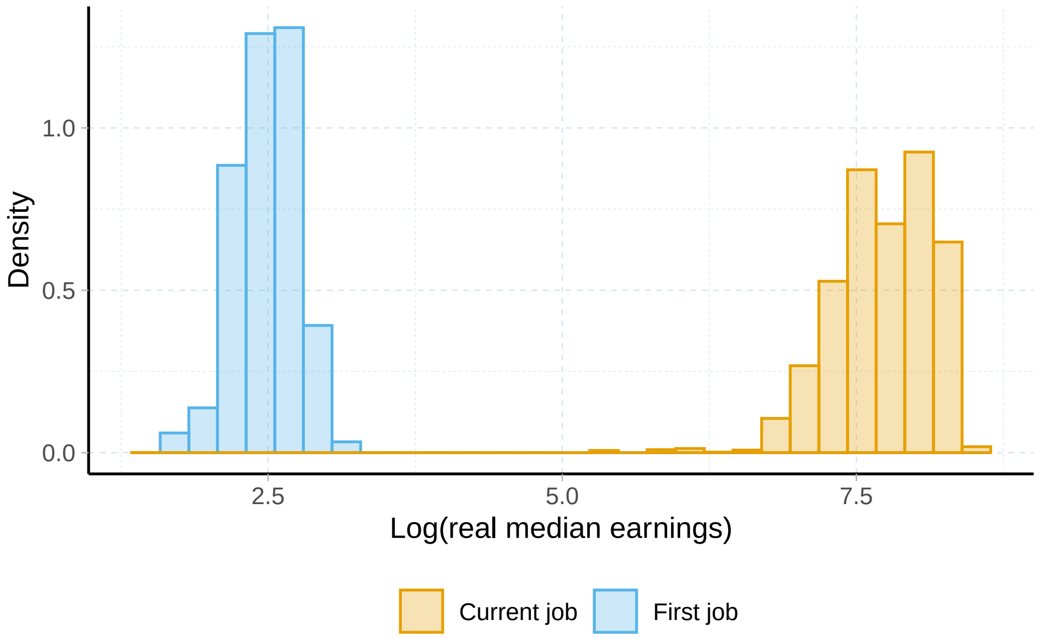
	Full sample			No parent job status			Has parent job status		
Variable	Mean	SD	N	Mean	SD	N	Mean	SD	N
Female	0.48	0.5	10728	0.426	0.495	4065	0.514	0.5	6663
Birthweight, g	3 316.7	533.4	10719	3 286.8	530	4061	3 335.2	534.7	6658
Parity	1.229	1.383	10716	1.429	1.53	4059	1.105	1.269	6657
Height of mother, cm	161.1	6.5	10631	160.5	6.4	4024	161.5	6.5	6607
Mother married	0.977	0.151	10716	0.969	0.172	4061	0.981	0.136	6655
Age of mother	26.218	5.463	10718	25.893	5.629	4059	26.419	5.348	6659
Age of father	29.032	6.423	8815	28.788	6.731	3173	29.173	6.234	5642
Age mother left edu	15.649	1.993	10660	15.299	1.715	4039	15.866	2.118	6621
Age father left edu	15.99	3.291	10306	15.62	2.472	3875	16.219	3.689	6431
Mother unemp at birth	0.945	0.227	7704	0.941	0.236	2920	0.948	0.222	4784
Father unemp at birth	0.03	0.171	10005	0.036	0.185	3741	0.027	0.161	6264
IQ at age 10	0.042	1.001	8615	-0.201	0.996	3197	0.187	0.976	5418

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

Appendix C Occupation ranking

The survey also codes job titles of respondents' current, last and first jobs using standard occupational classifications (SOC 1990, SOC 2000 and SOC 2010)[9]. The publicly available version of the dataset contains condensed versions of SOC codes: at 2-digit level in SOC 1990 and 3-digit level in SOC 2000 and SOC 2010 classifications.

I rank occupations using median real earnings of the relevant population. In subsections below, I describe the ranking procedure for the first and current/recent jobs.



Note: The figure plots the histogram of log real median earnings in first and current jobs of individuals in the UKHLS. The median earnings are defined at the 1-digit occupational code birth cohort. To rank first jobs I used median earnings of 18-21 year olds in same occupational group in the year the respondent turned 20 years. To rank current jobs I used median earnings of workers in the same birth cohort and occupational group in the UKHLS. For further details see Online Appendix C in the Online Appendix.

Figure C.1: Occupational ranking of first and current jobs in the UKHLS

Subsection C.1 Ranking first jobs

I base the ranking of first jobs on the median earnings of workers aged 18-21 in respective occupation and year. Since the analysis sample includes people born between 1950 and 1995, I need data on earnings of young adults between 1970 and 2015. I combine the General Household Survey (GHS), which ran between 1972 and 1994, and the aggregate tables based on the Annual Survey of Hours and Earnings (ASHE) released by the Office for National Statistics (ONS) from 1997 onwards.

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

The GHS is a microdata at the individual level including measure of gross annual earnings, occupational codes and basic socio-demograhpic characteristics. The aggregate tables based on the ASHE provide information on median gross annual earnings or workers by occupational code at 2-digit level, gender, full-time/part-time status, age group and year. In both datasets I restrict the sample to male full-time workers between ages 18-21.

Using the individual data in the GHS, I compute simple unweighted median earnings in each cell defined by occupational code and year of the survey. I deflate the median earnings by the Retail Price Index (RPI) in the corresponding year.

The occupational classifications used in the GHS and the ASHE tables vary over time. For example, between 1972 and 1977 the GHS reports occupations using the Classification of Occupations 1970, between 1985 and 1990 it uses Classification of Occupations 1980, and in 1991 it switched to Standard Occupational Classification 1990 (SOC 1990). The ASHE tables use SOC 1990 between 1997 and 2001, then SOC 2000 between 2002 and 2010, and SOC 2010 from 2011 onwards. Since the UKHLS does not provide any occupational codes in classifications from 1970 and 1980, I convert these codes to the SOC 1990 based on descriptions. The occupational codes in the SOC 1990, SOC 2000 and SOC 2010 classifications I leave unchanged.

The conversion between occupational classifications is not unique. For example, there are occupations in 1970 classification that correspond to multiple occupations in the SOC 1990 classification. I do not attempt to correct for these multiple matches, meaning that workers may be part of median earnings computation in multiple cells. To limit the influence of such conversion error, in the main analysis I group all occupational codes to 1-digit major group level. By doing so, I am implicitly assuming that occupations rarely change major groups, which approximately holds between SOC revisions (Figure C.2).

Finally, I merge each respondent in the analysis sample in the UKHLS with the median earnings of their first jobs in the year when respondents turned 20 years of age. When job codes are missing, I set the median earnings to zero. I then apply log and IHS transformation to the median earnings in real terms.

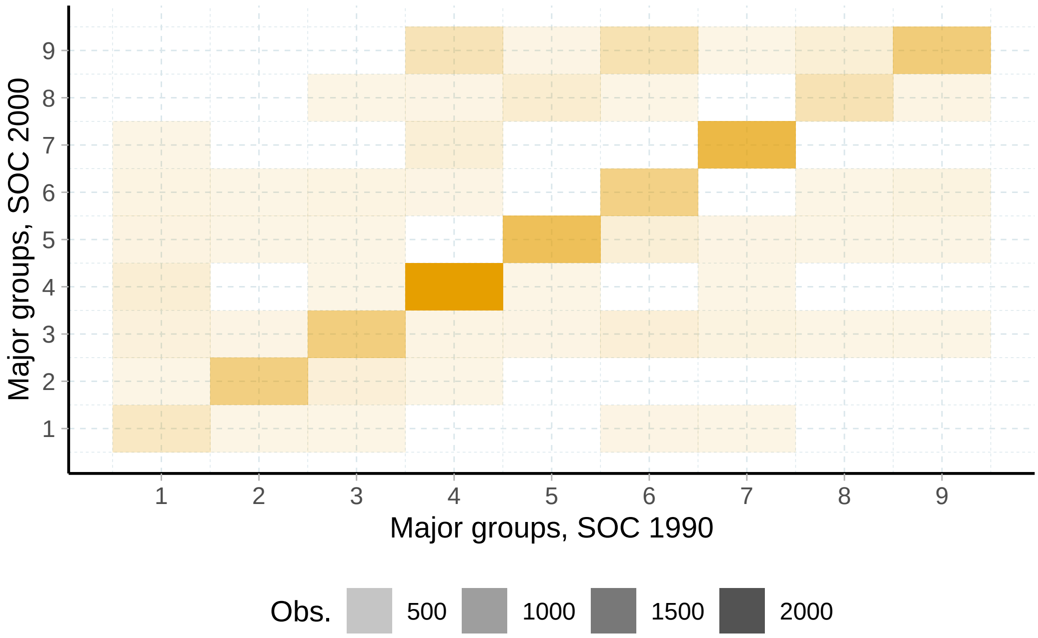
Subsection C.2 Ranking current jobs

Ranking the current jobs is much simpler since I can use the UKHLS itself to compute the median earnings and do not need to convert job codes between different classifications.

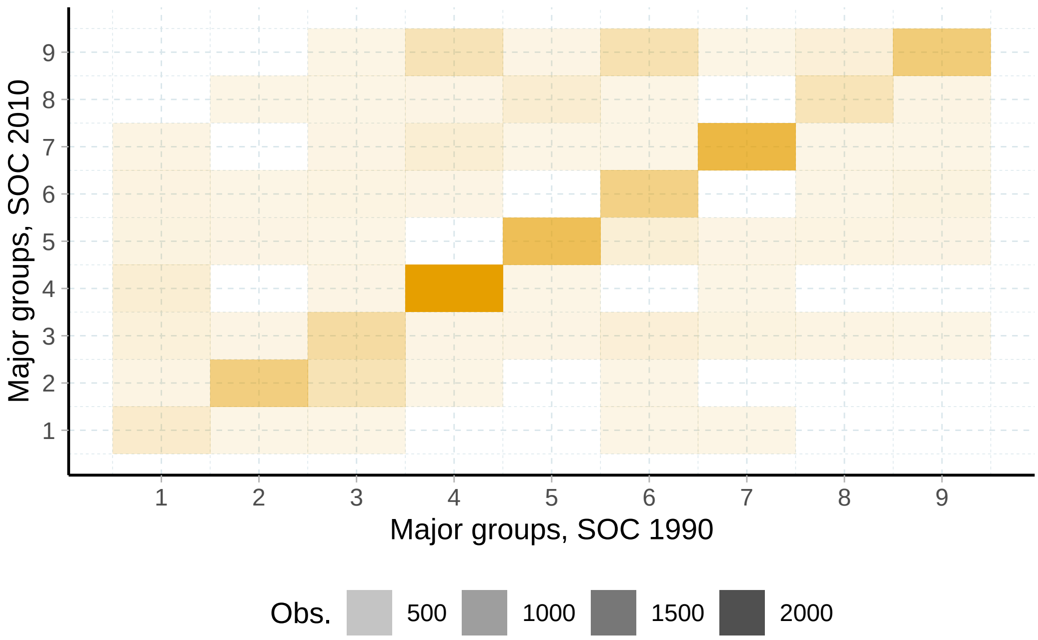
To remain consistent with the ranking of first jobs, I collapse the occupational codes of current jobs to 1-digit level. If someone is unemployed in wave 3, but had a job in the preceding two years, I use the occupational code of their last job. This adds job information for 2 273 out of 5 301 individuals with missing current job codes.

Using the sample of men working more than 25 hours a week, I compute weighted median earnings by year of birth and occupational code. When job code is missing, I set the median earnings to zero. I then deflate the median earnings with the CPI excluding rent, maintenance and water charges and apply log and IHS transformation to real median earnings.

For comparison, I do similar ranking based on 2-digit occupational codes both for first and current jobs. Table C.1 shows the correspondence between rankings based on 1-digit and 2-digits codes both for first and current jobs. Since there is no conversion error involved



(a) **SOC 1990 vs SOC 2000**



(b) **SOC 1990 vs SOC 2010**

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

Figure C.2: Distribution of one-digit major groups of first jobs by SOC

Table C.1: Comparison of job rankings based on 2-digit and 1-digit occupational codes

	Dependent variables	
	Log current job rank (1-digit)	Log first job rank (1-digit)
Log current job rank (2-digit)	0.536***	
	(0.030)	
Log first job rank (2-digit)		0.170***
		(0.010)
Obs.	15 395	14 706

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

Note: The table reports the results from regressions of log job ranks based on 1-digit codes on log job ranks based on 2-digit codes. 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.

in ranking the current jobs, I use the estimates from the first column as a benchmark. It is then clear that the conversion error in the occupational codes of first jobs significantly affects the job rankings.

Appendix D Validity of identifying assumptions

Subsection D.1 Test based on observed pre-determined characteristics

The causal interpretation of the estimation results relies on Assumption 1, akin to parallel trends assumption in the standard difference-in-differences setting. The assumption states that selection bias that determines in which families parents do not work does not vary with intelligence of children. The assumption is fundamentally untestable: I cannot observe outcomes of children with non-employed parents in the counterfactual world where their parents worked. However, I can provide supporting evidence based on observable characteristics that should not be affected by parental non-employment at age 14.

The idea is to use pre-determined characteristics as dependent variables in the regression Equation 1. Even though these variables should not be affected by parental non-employment, selection bias may render $\beta_1 \neq 0$. But the crucial test is whether $\beta_3 = 0$. Since I am measuring effect on pre-determined characteristics that are not influenced by parental non-employment, the causal effect is zero for everyone, regardless of intelligence score. Thus, $\beta_3 = 0$ is a necessary condition of Assumption 1.

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

Dependent variable	Parent non-emp	IQ	Parent non-emp × IQ	Obs.	Mean outcome
At birth					
Parity	0.444***	-0.069***	0.024	5 063	1.5
	(0.094)	(0.022)	(0.085)		
Lactation attempted	-0.049**	0.031***	-0.026	5 063	0.322
	(0.024)	(0.008)	(0.024)		
Birthweight, g	-60.310*	57.119***	-10.030	5 059	3 283.7
	(35.011)	(9.956)	(30.745)		
Age of mother	0.575*	0.378***	0.380	5 063	26.2
	(0.325)	(0.082)	(0.307)		
Age of father	1.807***	0.440***	0.760	4 405	29.0
	(0.424)	(0.102)	(0.375)		
Height of mother, cm	-1.131***	0.346***	-0.033	5 029	160.7
	(0.369)	(0.109)	(0.326)		
Mother married	-0.015	-0.001	-0.005	5 063	0.958
	(0.016)	(0.004)	(0.013)		
Age of mother at first birth	-0.621***	0.485***	0.013	5 043	21.7
	(0.217)	(0.061)	(0.204)		
At age 5					
Composite score (PC1)	-0.123	0.267***	0.020	2 134	-0.0455
	(0.088)	(0.037)	(0.072)		

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

Dependent variable	Regressors			Obs.	Mean outcome
	Parent non-emp	IQ	Parent non-emp $\times$ IQ		
Father's mother born UK	-0.006	-0.002	0.004	20 307	0.755
	(0.007)	(0.002)	(0.006)		
Father's father born UK	-0.011	0.002	0.007	20 307	0.745
	(0.007)	(0.002)	(0.006)		
Mother's mother born UK	-0.001	0.001	-0.003	20 307	0.769
	(0.006)	(0.002)	(0.006)		
Mother's father born UK	-0.009	0.005***	0.001	20 307	0.757
	(0.007)	(0.002)	(0.007)		
Has siblings	0.004	-0.001	-0.006	20 307	0.900
	(0.009)	(0.003)	(0.008)		
White british father	0.010	0.000	-0.009	20 307	0.670
	(0.010)	(0.003)	(0.009)		
White british mother	0.014	-0.003	-0.006	20 307	0.676
	(0.010)	(0.003)	(0.010)		

†p < 0.1; ††p < 0.05; †††p < 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 shows the results from regressions of predetermined variables in UKHLS shown in the first column on parental non-employment and intelligence score. All regressions control for respondents' (gender, year of birth, country of birth, race, immigrant status) and parents' (highest educational qualifications and country of birth) characteristics. Standard errors are reported in parentheses.

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

Dependent variable	Parent non-emp	IQ	Parent non-emp × IQ	Obs.	Mean outcome
Age at test, days	-0.771	-0.586	2.064	4 497	1 852.8
	(2.085)	(0.929)	(1.613)		
Reading score	-0.523	1.448***	-0.898	2 215	3.1
	(0.353)	(0.170)	(0.359)		
English picture vocab. score	-0.349***	0.375***	0.012	4 587	-0.345
	(0.091)	(0.025)	(0.084)		
Copying designs score	-0.052	0.393***	0.089	4 587	-0.0981
	(0.062)	(0.017)	(0.056)		
Draw-a-man score	-0.109	0.288***	0.055	4 587	-0.172
	(0.077)	(0.020)	(0.078)		
Complete-a-profile score	-0.330	0.480***	0.016	4 431	6.85
	(0.258)	(0.072)	(0.251)		
At age 10					
Has normal vision	-0.033	0.005	0.000	4 800	0.864
	(0.023)	(0.006)	(0.023)		
At age 16					
Composite score (PC1)	-0.178*	0.579***	0.129	1 297	-0.0685
	(0.100)	(0.026)	(0.103)		
Spelling score	-2.178	14.864***	2.697	5 063	74.1
	(4.753)	(1.365)	(4.205)		
Vocabulary score	-0.872	6.146***	-0.584	5 063	19.6
	(1.284)	(0.381)	(1.162)		
Reading score	-2.791**	7.387***	2.646	1 377	53.6
	(1.368)	(0.351)	(1.459)		
Math score	-0.185	6.102***	0.946	1 643	36.1
	(1.099)	(0.287)	(1.175)		
Complete-matrix score	-0.285*	0.575***	0.034	1 412	8.81
	(0.172)	(0.048)	(0.212)		

†p < 0.1; ††p < 0.05; †††p < 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 shows the results from regressions of predetermined variables shown in the first column on parental non-employment at age 16 and intelligence score at age 10 in the BCS70. All regressions control for respondents' (gender, country of birth) and parents' (country of birth and age left education) characteristics. Estimations are weighted with inverse probability of response (Mostafa and Wiggins 2014). Standard errors are reported in parentheses.

Table D.1 presents the regression results using a set of predetermined characteristics available in the UKHLS. Indeed, all the interaction coefficients are statistically insignificant and close to zero in magnitude. However, the set of predetermined variables available for the test in the UKHLS is rather limited: they are mostly related to ethnic background of parents and grandparents, which could already be captured by parents' country of birth and immigrant status indicators in $\mathbf{P}_i$ and $\mathbf{X}_i$. This explains nil main effects of parental non-employment and intelligence on the pre-determined characteristics seen in second and third columns of the table.

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

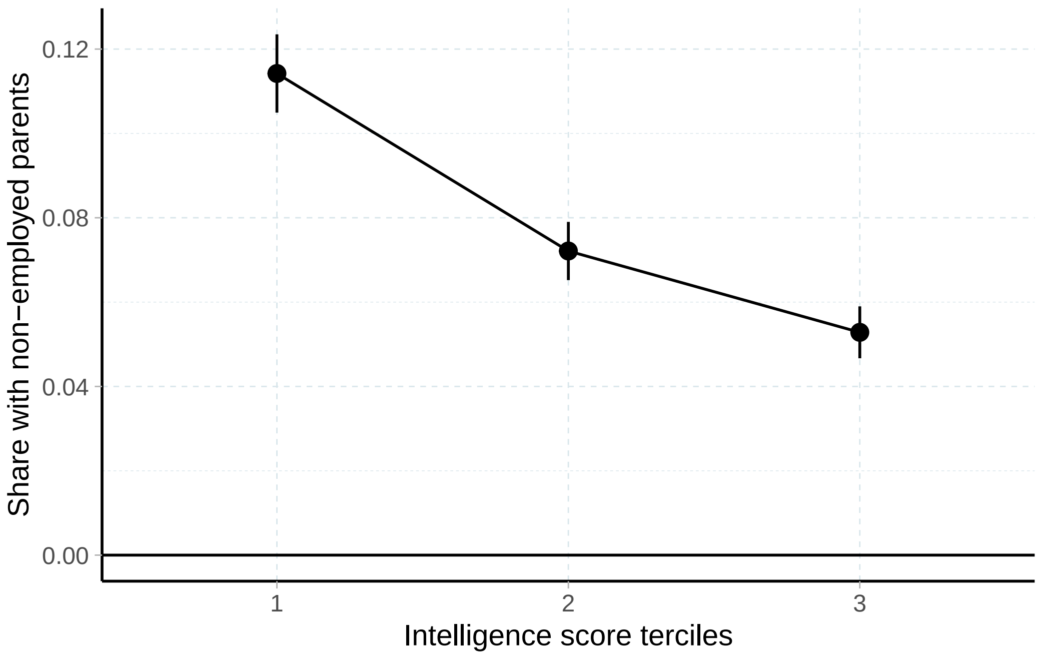
Subsection D.2 Intergenerational persistence of intelligence

In this section I examine what does the parallel trends assumption imply in terms of differential non-employment probabilities and intergenerational process on intelligence. As mentioned earlier, this assumption requires the selection bias to be constant across intelligence distribution. But it is not clear whether the assumption still holds knowing that parental non-employment probabilities vary with intelligence. Parents with high intelligence scores are more likely to work. They are also more likely to have high-intelligence children. It is not clear how these two facts affect Assumption 1.

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

Let's consider the intergenerational persistence of intelligence score more closely. I start with the binary intelligence case. For clarity, denote the intelligence score of the child as IQ_C and that of the parent as IQ_P. The persistence of intelligence score is then governed by two parameters $q_1 \equiv \Pr(IQ_C = 1|IQ_P = 1)$ and $q_0 \equiv \Pr(IQ_C = 1|IQ_P = 0)$. Then, intelligence has positive persistence if $q_1 > q_0$. I also allow persistence to vary with parent's intelligence, i.e., q_1 and q_0 do not necessarily add up to one.

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



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

Figure D.1: Parental non-employment by intelligence

of each other

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

Assumption 1 can be rewritten with parental intelligence as a pre-treatment outcome:

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

After applying Bayes rule and rearranging the terms, Equation (D.1) can be rewritten as

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

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

The ratio on the left-hand side of Equation (D.2) describes persistence of the intelligence score between generations.

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

I study the condition in Equation (D.2) numerically by evaluating it at all plausible combinations of parameters q_0, q_1, u_0, u_1 and p. I define the set of plausible combinations using the following constraints:

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

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

Panel A of Figure D.2 shows the simulation results in the binary intelligence case. When Equation (D.2) holds, the difference between the left- and right-hand side is zero. The figure, therefore, plots the average value of this difference for each combination of persistence parameters q_0 and q_1 (averaging across all plausible values of u_0 and u_1). The cells with values close to 0 (coloured white) are the parameter combinations that on average are closest to satisfy the parallel trends assumption. The black line traces the parameter combinations that imply constant persistence of intelligence; values below the line correspond to decreasing and above - increasing persistence of intelligence. Thus, the numerical analysis shows that Assumption 1 tends to hold when intergenerational persistence is marginally stronger at the bottom of the intelligence score distribution.

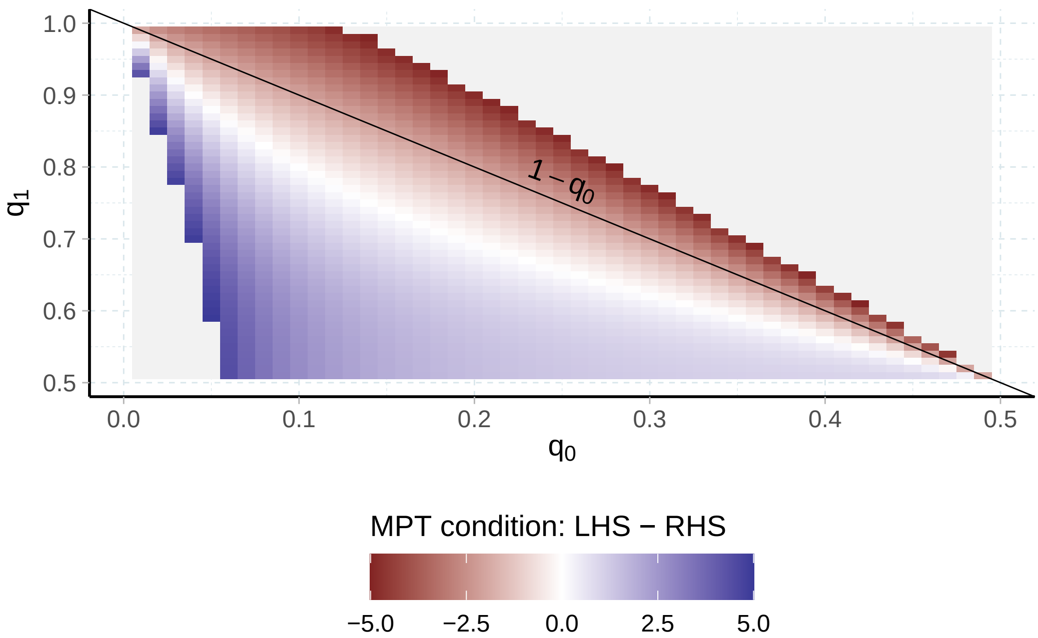
A similar analysis can be done in the case of continuous intelligence score. Assumption 1 can be written as

$$\frac{\mathrm{Cov}(IQ_C, IQ_P|UP = 1)}{\mathrm{Var}(IQ_C|UP = 1)} = \frac{\mathrm{Cov}(IQ_C, IQ_P|UP = 0)}{\mathrm{Var}(IQ_C|UP = 0)} \tag{D.3}$$

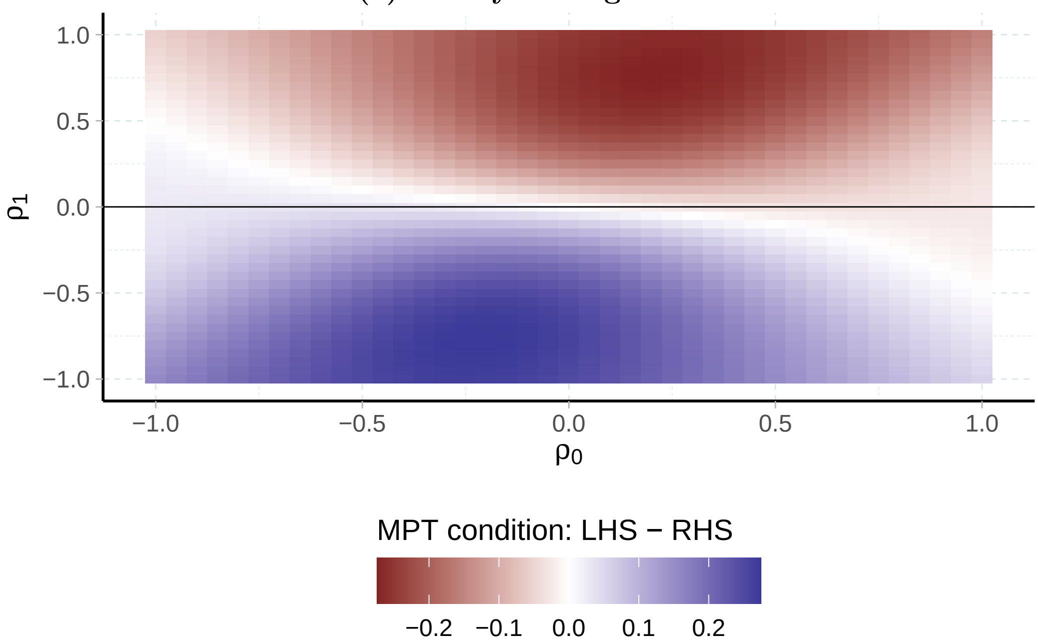
To analyse the condition in Equation (D.3), I need to specify the distribution of the parental intelligence score and two CEFs: $\mathbb{E}(IQ_C|IQ_P)$ and $\mathbb{E}(UP|IQ_P) = \Pr(U = 1|IQ_P)$. I assume that parental intelligence is drawn from a standard normal distribution $IQ_P \sim \mathcal{N}(0, 1)$. I also assume that intergenerational process on intelligence follows an AR(1) process, where persistence parameter is itself a function of parental intelligence.

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

I parameterise both the persistence parameter and the conditional non-employment probability as linear functions of intelligence



(a) **Binary intelligence**



(b) **Continuous intelligence**

Note: The figure plots the average value of Equation (D.2) for each combination of persistence parameters in discrete (panel A) and continuous (panel B) intelligence cases. The black line corresponds to constant persistence frontier. Parameter combinations below the black line imply that persistence decreases with intelligence, and those above - that persistence increases with intelligence.

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

$$\rho(IQ_P) = \rho_0 + \rho_1 IQ_P$$
$$\Pr(U = 1|IQ_P) = \mu_0 + \mu_1 IQ_P$$

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

The results of the simulation are shown in Panel B of Figure D.2 and are similar to those in the discrete case. Assumption 1 tends to hold when intergenerational persistence is flat at moderate values of positive persistence or stronger at the bottom for very high positive persistence at the mean.

In addition to numerical analysis, some empirical evidence on intergenerational persistence can be glimpsed from the BCS70 dataset. The dataset includes both cognitive assessment of cohort members (parents) and their children (see Online Appendix B for more details). I divide parent-child pairs according to the age of child at the time of assessment: 3-5, 6-8, 9-11, 12-14 and 15-16. In each of these age groups, I regress children's standardized intelligence score on a quadratic polynomial of parents' intelligence score measured at the time parents were 10 years old. The results are shown in Table D.3. On average persistence is positive, consistent with the existing evidence in the literature. The results also suggest that persistence may be slightly decreasing with intelligence. However, this result should be taken with a grain of salt in view of small sample size and potentially non-random sample attrition, response to cognitive assessment and fertility outcomes.

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

Subsection D.3 Selection based on unobservables

In this section I discuss potential selection into parental non-employment based on unobservables. Although the tests based on observable characteristics in the UKHLS and the BCS70 in Online Appendix D.1 are consistent with Assumption 1, there is still concern that some unobservable factor may simultaneously determine parental non-employment, children's intelligence and other outcomes. To address this issue, I examine sensitivity of the results to correlation structure of error terms.

Consider the following system of equations

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

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

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

$$
\begin{aligned}
UP_i &= \mathbf{Z}_i\boldsymbol{\alpha} + IQ_i\alpha_{IQ} + u_i \\
IQ_i &= \mathbf{Z}_i\boldsymbol{\gamma} + v_i \\
Y_i &= \mathbf{Z}_i\boldsymbol{\beta} + \beta_{UP}UP_i + \beta_{IQ}IQ_i + \beta_{UP\times IQ}UP_iIQ_i + \varepsilon_i
\end{aligned} \tag{D.4}
$$

where

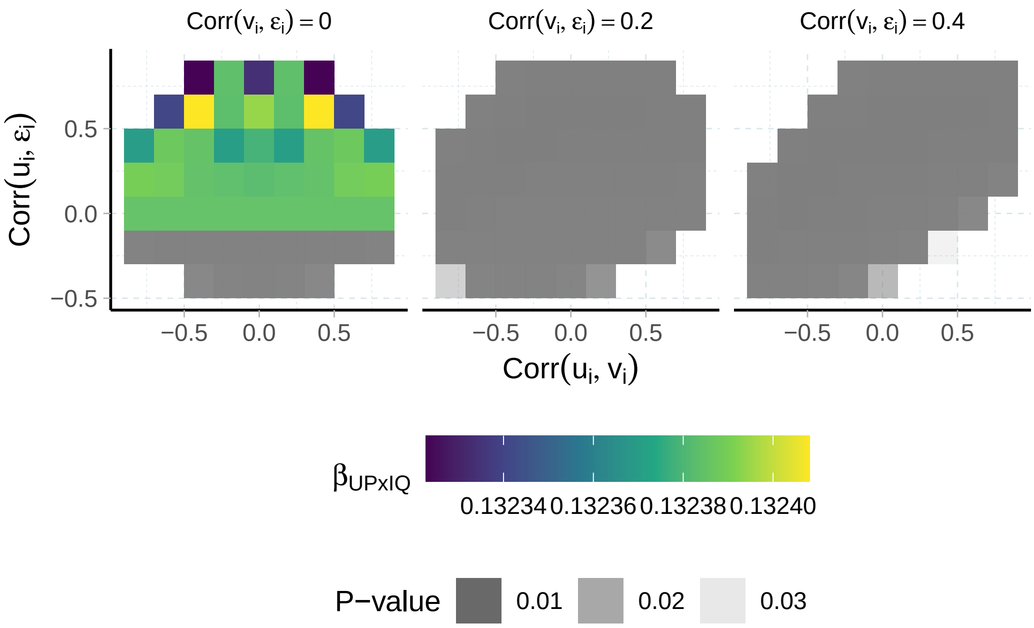
$$
\begin{pmatrix} u_i \\ v_i \\ \varepsilon_i \end{pmatrix} \sim \mathcal{N}\left(\begin{pmatrix} 0 \\ 0 \\ 0 \end{pmatrix}, \begin{pmatrix} \sigma_u^2 & \mathrm{Cov}(u_i, v_i) & \mathrm{Cov}(u_i, \varepsilon_i) \\ \mathrm{Cov}(u_i, v_i) & \sigma_v^2 & \mathrm{Cov}(v_i, \varepsilon_i) \\ \mathrm{Cov}(u_i, \varepsilon_i) & \mathrm{Cov}(v_i, \varepsilon_i) & \sigma_\varepsilon^2 \end{pmatrix}\right)
$$

Due to computational limitations, I assume that all equations in the system are linear with normally distributed error terms. I also restrict the set of covariates $\mathbf{Z}_i$ to dummy variables for gender, race, 5-year birth cohort groups and highest parental qualifications. In this exercise, I focus on IHS real monthly earnings as main outcome variable Y.

The idea is to estimate the system in Equation (D.4) while fixing the parameters of the variance-covariance matrix of the error terms. In particular, I first run the equations separately to estimate values $\sigma_u^2, \sigma_v^2, \sigma_\varepsilon^2$. I then estimate Equation (D.4) for different values of correlations between the error terms, which together with variances define the $\mathrm{Cov}(u_i, v_i), \mathrm{Cov}(u_i, \varepsilon_i), \mathrm{Cov}(v_i, \varepsilon_i)$.

Informally, I assume that the observed data came from a data-generating process with a particular correlation structure that I fix exogenously. The exercise then shows how would the estimated coefficients change.

Figure D.3 plots the results of the sensitivity analysis. The three panels correspond to different values of correlations between unobserved terms in IQ and Y equations. Similarly, the x axis corresponds to different correlation values between error terms in UP and IQ, while y axis - correlations between error terms in UP and Y equations. The colour of cells corresponds to the estimated coefficients of the interaction term $\beta_{UP\times IQ}$. Grey cells indicate results from regressions where main effects have wrong signs, i.e. $\beta_{UP} \geq 0$ or $\beta_{IQ} \leq 0$. Empty cells mean that estimation for that particular combination of correlation measures did not converge.



Note: The figure plots estimated coefficients of the interaction term $\beta_{UP\times IQ}$ obtained after fitting the system in Equation (D.4) under different assumptions about the correlation structure of the error terms. The regressions control for gender, race, 5-year birth cohort groups and highest parental qualifications. The regressions were weighted and standard errors clustered at the sampling level. Grey cells correspond to estimations where main effects β_{UP} or β_{IQ} were of the wrong sign.

Figure D.3: Sensitivity of estimated results to unobserved correlation structure

While Figure D.3 makes it clear that correlation structure of error terms has strong influence on whether the system can be estimated and on estimates of the main effects, the coefficients of the interaction term are remarkably stable. This is explained by the conditional variance-covariance matrix being identical between the groups with $UP = 1$ and $UP = 0$.

$$\begin{pmatrix} v_i \\ \varepsilon_i \end{pmatrix} \Bigg| u_i = a \sim \mathcal{N}\left(M, \begin{pmatrix} \sigma_v^2 - \frac{\text{Cov}(v_i,u_i)^2}{\sigma_u^2} & \text{Cov}(v_i,\varepsilon_i) - \frac{\text{Cov}(u_i,\varepsilon_i)\text{Cov}(u_i,v_i)}{\sigma_u^2} \\ \text{Cov}(v_i,\varepsilon_i) - \frac{\text{Cov}(u_i,\varepsilon_i)\text{Cov}(u_i,v_i)}{\sigma_u^2} & \sigma_\varepsilon^2 - \frac{\text{Cov}(\varepsilon_i,u_i)^2}{\sigma_u^2} \end{pmatrix}\right)$$

where $M = \frac{a}{\sigma_u^2}\begin{pmatrix} \text{Cov}(u_i, v_i) \\ \text{Cov}(u_i, \varepsilon_i) \end{pmatrix}$.

In sum, all pieces of evidence suggest that Assumption 1 is not unreasonable. Tables D.1 and D.2 show that selection bias measured in terms of the observed pre-determined characteristics do not vary with intelligence of children. Analysis in Online Appendix D.2 addresses the concern that intergenerational process on intelligence and its correlation with economic outcomes may bias the estimations. While this is a valid concern and it may indeed bias the results, the simulation exercise suggests that at moderately positive correlations between intelligence of children and parents, Assumption 1 holds when intergenerational persistence is linear. I also provide some evidence in the BCS70, as well as references to the literature, that support the claim of moderately positive linear persistence in cognitive abilities. Finally, to address the concern that unobserved factors may simultaneously determine parental non-employment, children's intelligence and outcomes, I consider sensitivity of the estimated effects to the correlation structure of the error terms. The exercise shows that while main effects are highly sensitive to the correlation specification, the coefficient of the interaction term remains remarkably robust.

Subsection D.4 Intelligence as outcome of parental non-employment

The causal interpretation of β_3 in Equation 1 relies on intelligence of children not being as well an outcome of parental non-employment. The reader might be sceptical of this assumption, especially in light of the recent evidence in Carneiro et al. (2021) showing that higher family income during adolescent years increases intelligence of children. I cannot directly test the assumption since the measure of parental non-employment in the UKHLS or the BCS70 is non-random and may be correlated with intelligence. Nevertheless, I argue that β_3 can still have a causal interpretation with slight adjustment and supporting evidence in Table D.2 remains valid.

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

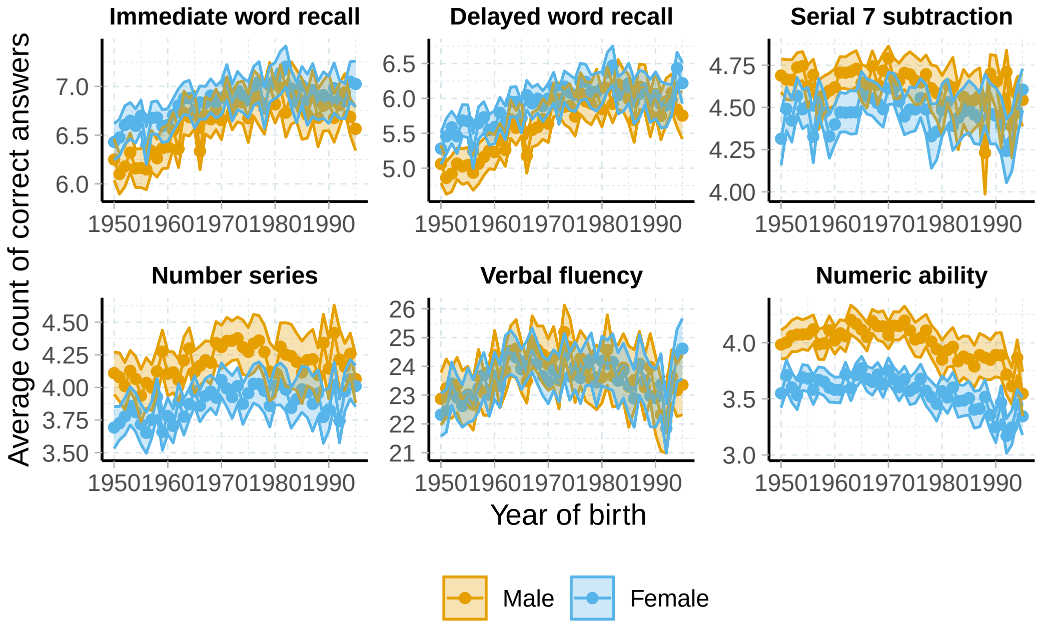
$$\begin{aligned}
\beta_3 &= \frac{Cov(y, IQ|UP=1)}{Var(IQ|UP=1)} - \frac{Cov(y, IQ|UP=0)}{Var(IQ|UP=0)} = \\
&= \frac{Cov(y^1, IQ^1|UP=1)}{Var(IQ^1|UP=1)} - \frac{Cov(y^0, IQ^0|UP=0)}{Var(IQ^0|UP=0)} = \\
&= \underbrace{\frac{Cov(y^1 - y^0, IQ^1|UP=1)}{Var(IQ^1|UP=1)}}_{\text{Causal effect}} + \underbrace{\frac{Cov(y^0,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

The first term describes how causal effect of parental non-employment changes with intelligence of children evaluated among children whose parents were not working The second term reflects the bias stemming from changes in the composition of families where parents do or do not work. Note that if intelligence is indeed an outcome of parental non-employment, the bias term may not be equal to zero even if parental non-employment were randomly assigned.

There is a slight change in the causal effect: it is measuring the differential impact of parental non-employment as IQ^1 increases, instead of IQ. In other words, the estimator can only identify changes in the causal effect in the event that parents do not work. Intelligence may have affected the outcomes of these children differently had their parents kept their jobs. The main goal of this paper is to investigate how parental non-employment effects vary across intelligence of children. For this purpose the change in the interpretation is a minor one. However, it restricts the ability to provide policy-relevant statement of what would have happened in the counterfactual world where the parents of the affected children stayed employed. The estimated results could still speak to that, if potential outcomes depend on IQ^1 in the same way as on IQ^0.

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

Appendix E Intelligence



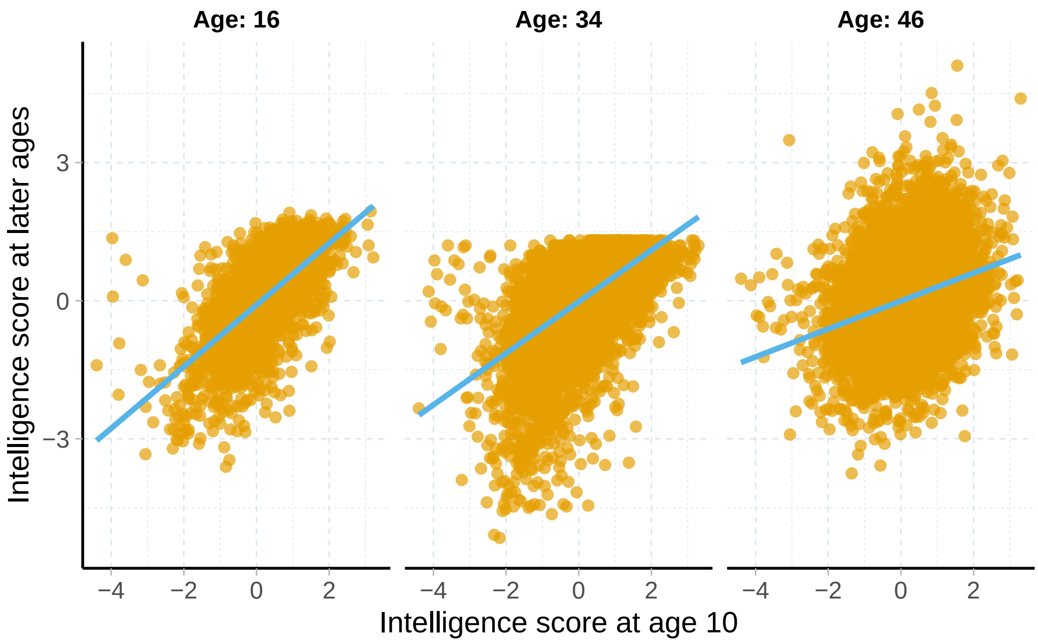
Note: The figure plots the average raw test scores in each test by year of birth and gender of respondents. The shaded areas correspond to 95% confidence interval. The statistics are weighted by the cross-sectional response weights.

Figure E.1: Cognitive test results

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

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

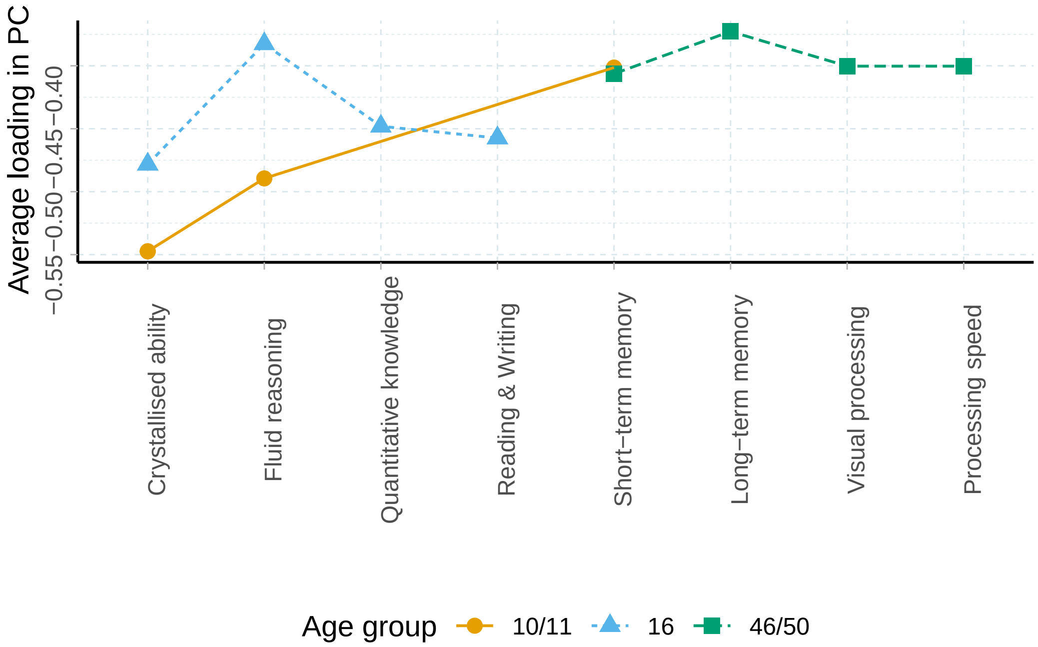
By using intelligence score measured later in life I am implicitly assuming that relative position of children along the distribution remains stable over time: a smarter child is also a smarter adult. Of course, the level of skills does not stay constant over the life cycle (Salthouse 2010). But the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



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

Figure E.2: Stability of intelligence score by ages

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

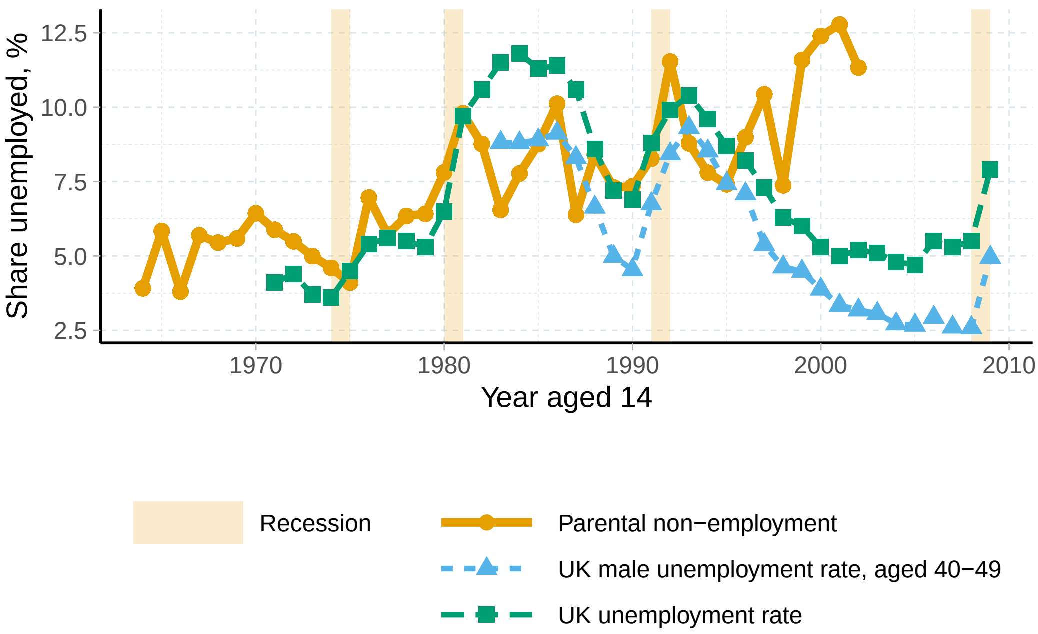


Note: The plot shows cognitive domains of tests administered at different ages. On the y-axis I plot simple average of test scores' loadings in PC1 in a given domain and age group.

Figure E.3: Cognitive domains of tests by ages

Appendix F Additional robustness checks

Subsection F.1 Measures of parental non-employment



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

Figure F.1: Parental non-employment and aggregate economy

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

Table F.1: Robustness to non-employment measures

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

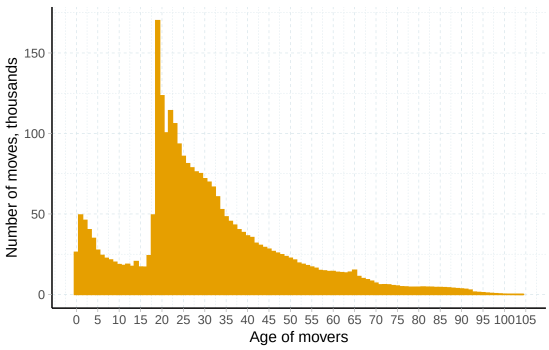
†p < 0.1; ††p < 0.05; †††p < 0.01 based on FDR adjusted q-values
*p <0.1; **p <0.05; ***p <0.01 based on conventional p-values

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

Subsection F.2 Non-employment vs poverty

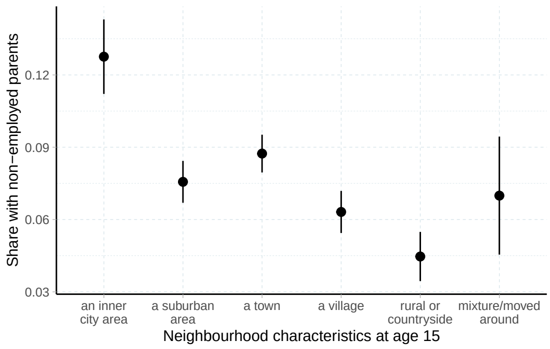
Another concern is that the current measure of parental non-employment does not differentiate between job loss and long-term non-participation in the labour force or poverty. The pre-determined characteristics of children and parents in $\mathbf{X}_i$ and $\mathbf{P}_i$, respectively, in Equation 1 should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

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



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

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



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

Figure F.3: Neighbourhood characteristics at age 15 and parental non-employment

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

Table F.2: Neighbourhood characteristics at age 15, parental non-employment and IQ

	Dependent variable
	Inner city
Parent nonemp	0.047***
	(0.011)
IQ	-0.015***
	(0.003)
Parent nonemp × IQ	0.007
	(0.010)
Obs.	20 303

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

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

Subsection F.3 Replication in the BCS70

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

Table F.3: Replication in the BCS70

	Post-16 school	Degree	Work	%Δ earnings
UKHLS sample born in 1970				
Parent nonemp	-0.026	0.127***	-0.007	-0.079
	(0.034)	(0.017)	(0.016)	(0.236)
IQ	0.129***	0.160***	0.031***	0.267***
	(0.009)	(0.008)	(0.007)	(0.079)
Parent nonemp × IQ	-0.051†	-0.004	0.106†††	0.197
	(0.026)	(0.014)	(0.016)	(0.222)
Obs.	578	578	578	578
BCS70 at age 26				
Parent nonemp	-0.039	-0.044***	-0.146***	-0.564***

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Table F.3: Replication in the BCS70 (Continued)

	Post-16 school	Degree	Work	%Δ earnings
	(0.024)	(0.013)	(0.030)	(0.113)
IQ	0.119***	0.096***	0.048***	0.234***
	(0.007)	(0.006)	(0.009)	(0.030)
Parent nonemp × IQ	-0.055††	-0.072†††	0.028	0.078
	(0.020)	(0.011)	(0.027)	(0.089)
Obs.	5 029	4 901	5 063	4 780
BCS70 at age 30				
Parent nonemp	-0.055*	-0.045***	-0.119***	-0.476***
	(0.031)	(0.017)	(0.027)	(0.160)
IQ	0.141***	0.113***	0.026***	0.162***
	(0.009)	(0.006)	(0.006)	(0.043)
Parent nonemp × IQ	-0.026	-0.060†††	0.082†††	0.280†
	(0.027)	(0.016)	(0.027)	(0.145)
Obs.	4 047	5 056	4 170	1 886
BCS70 at age 34				
Parent nonemp		-0.023	-0.086***	-0.639***
		(0.020)	(0.026)	(0.182)
IQ		0.102***	0.024***	0.205***
		(0.006)	(0.006)	(0.054)
Parent nonemp × IQ		-0.039†	0.087†††	0.210
		(0.018)	(0.028)	(0.170)
Obs.		5 063	3 757	1 375
BCS70 at age 38				
Parent nonemp		0.013	-0.044*	-0.190
		(0.032)	(0.026)	(0.145)
IQ		0.135***	0.019***	0.253***
		(0.009)	(0.007)	(0.041)
Parent nonemp × IQ		-0.005	0.023	-0.065
		(0.026)	(0.028)	(0.153)
Obs.		3 555	3 542	3 148

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

Subsection F.4 Variations in exposure

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

Table F.4: Robustness to variations in exposure to parental non-employment

	Post-16 school	Degree	Work	%Δ earnings	%Δ hourly wage	Hours
White British						
Parent nonemp	-0.079***	-0.035***	-0.059***	-0.271***	-0.115***	-2.683***
	(0.014)	(0.013)	(0.014)	(0.048)	(0.029)	(0.542)
IQ	0.140***	0.131***	0.051***	0.289***	0.162***	1.788***
	(0.004)	(0.004)	(0.004)	(0.014)	(0.009)	(0.157)
Parent nonemp × IQ	-0.035††	-0.039†††	0.052†††	0.145†††	-0.050†	1.703†††
	(0.013)	(0.011)	(0.014)	(0.044)	(0.028)	(0.497)
Obs.	18 176	18 176	18 176	18 176	14 209	18 176
Outcome mean	0.36	0.27	0.75	2.68	0.16	26.03
Outcome sd	0.48	0.44	0.43	1.63	0.16	17.54
Born in England						
Parent nonemp	-0.080***	-0.036**	-0.055***	-0.264***	-0.123***	-2.690***
	(0.016)	(0.016)	(0.016)	(0.050)	(0.031)	(0.614)
IQ	0.135***	0.130***	0.051***	0.292***	0.158***	1.875***
	(0.004)	(0.004)	(0.005)	(0.015)	(0.009)	(0.179)
Parent nonemp × IQ	-0.034††	-0.035††	0.055†††	0.148†††	-0.045	1.634†††
	(0.014)	(0.013)	(0.015)	(0.045)	(0.030)	(0.547)
Obs.	15 222	15 222	15 222	15 222	11 742	15 222
Outcome mean	0.35	0.28	0.75	2.66	0.16	25.83
Outcome sd	0.48	0.45	0.44	1.64	0.16	17.57
Born in Wales						
Parent nonemp	-0.095	-0.040	-0.095	-0.332*	-0.049	-2.391
	(0.074)	(0.056)	(0.080)	(0.197)	(0.067)	(3.228)
IQ	0.139***	0.131***	0.060***	0.301***	0.228***	1.830**
	(0.020)	(0.017)	(0.021)	(0.048)	(0.051)	(0.825)
Parent nonemp × IQ	-0.045	-0.060	0.031	0.171	-0.134	2.670
	(0.053)	(0.042)	(0.070)	(0.148)	(0.078)	(2.032)
Obs.	1 337	1 337	1 337	1 337	1 003	1 337
Outcome mean	0.37	0.23	0.72	2.53	0.15	25.34
Outcome sd	0.48	0.42	0.45	1.67	0.15	18.23
Born in Scotland						

Continued on next page

Table F.4: Robustness to variations in exposure to parental non-employment (Continued)

	Post-16 school	Degree	Work	%Δ earn-ings	%Δ hourly wage	Hours
Parent nonemp	-0.076	-0.047	-0.078	-0.350***	-0.085	-3.262
	(0.057)	(0.051)	(0.053)	(0.134)	(0.071)	(2.022)
IQ	0.170***	0.141***	0.053***	0.327***	0.171***	1.681**
	(0.016)	(0.014)	(0.017)	(0.046)	(0.028)	(0.760)
Parent nonemp × IQ	-0.012	0.001	0.044	0.098	-0.181††	2.079
	(0.063)	(0.046)	(0.060)	(0.139)	(0.068)	(2.125)
Obs.	1 927	1 927	1 927	1 926	1 502	1 927
Outcome mean	0.48	0.26	0.74	2.68	0.16	25.95
Outcome sd	0.50	0.44	0.44	1.63	0.11	17.80
Born in NI						
Parent nonemp	-0.042	-0.024	-0.082	-0.290*	0.007	-2.695
	(0.157)	(0.125)	(0.147)	(0.165)	(0.091)	(5.458)
IQ	0.149***	0.109**	0.100*	0.434***	0.142***	3.604*
	(0.055)	(0.047)	(0.052)	(0.051)	(0.020)	(1.950)
Parent nonemp × IQ	-0.043	0.000	-0.089	-0.255	0.104	-3.186
	(0.144)	(0.120)	(0.116)	(0.146)	(0.093)	(4.261)
Obs.	1 436	1 436	1 436	1 434	1 091	1 436
Outcome mean	0.51	0.26	0.73	2.58	0.14	24.83
Outcome sd	0.50	0.44	0.45	1.63	0.10	17.34

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

Therefore, I repeat the estimations in the sample that is restricted to white British individuals only in the first panel of Table F.4. The results are very similar to the main results reported in Tables 3 and 5.

Another possible concern is that institutional environment is not uniform within the UK. For example, Online Appendix A has touched upon differences in high-school exams and university admissions between England and Scotland. Therefore, the second through fifth panels of Table F.4, I repeat the estimations separately by UK country of birth: England, Scotland, Wales and Northern Ireland (NI). Again the estimates among individuals born in England and Wales are very similar to the main results. Interestingly, the estimates of the interaction effect on educational outcomes are smaller in magnitude when I restrict the estimation sample to those born in Scotland. This result is consistent with education system in Scotland being less selective. The results among individuals born in Northern

Ireland are the most surprising. Here, higher intelligence individuals exposed to non-employed parents are relatively unaffected in terms of educational outcomes, but are heavily penalized in the labour market.

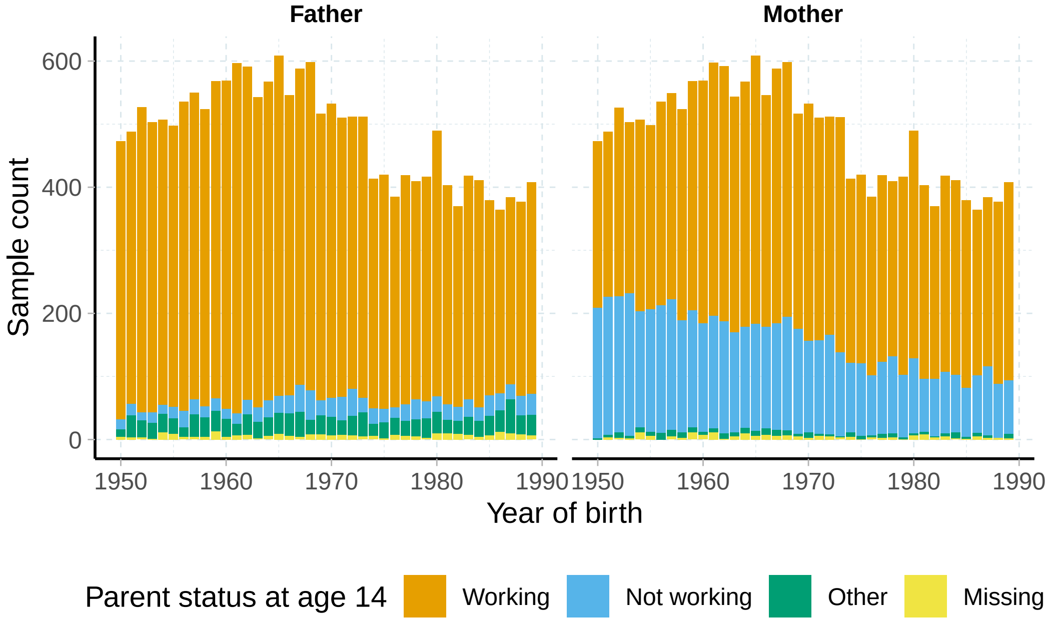
Appendix G Supplementary Figures and Tables

Table G.1: UKHLS descriptive statistics and missing intelligence score

	Full sample			Non-missing intelligence			Missing intelligence				
Variable	Mean	SD	N	Mean	SD	N	Mean	SD	N	Diff	SE
Age	40.250	12.975	22779	40.174	12.929	21208	41.266	13.532	1571	$-1.092^{\dagger\dagger}$	0.450
Female	0.513	0.500	22779	0.510	0.500	21208	0.551	0.498	1571	$-0.041^{\dagger\dagger\dagger}$	0.015
British	0.937	0.242	22432	0.939	0.239	20892	0.915	0.279	1540	$0.024^{\dagger\dagger\dagger}$	0.007
Parents w/ degree	0.145	0.352	18652	0.148	0.355	17472	0.096	0.295	1180	$0.052^{\dagger\dagger\dagger}$	0.011
School-leaving age	16.589	1.143	22657	16.612	1.134	21102	16.288	1.222	1555	$0.324^{\dagger\dagger\dagger}$	0.045
Post-16 school	0.360	0.480	22779	0.369	0.482	21208	0.242	0.428	1571	$0.127^{\dagger\dagger\dagger}$	0.016
Degree	0.258	0.438	22779	0.267	0.442	21208	0.146	0.353	1571	$0.121^{\dagger\dagger\dagger}$	0.012
Work	0.726	0.446	22779	0.735	0.441	21208	0.605	0.489	1571	$0.13^{\dagger\dagger\dagger}$	0.016
Self empl	0.090	0.287	22779	0.091	0.288	21208	0.078	0.268	1571	0.014	0.009
IHS earnings	2.586	1.659	22779	2.630	1.645	21208	2.004	1.727	1571	$0.625^{\dagger\dagger\dagger}$	0.057
Earn > 0	0.757	0.429	22779	0.768	0.422	21208	0.614	0.487	1571	$0.154^{\dagger\dagger\dagger}$	0.016
Earn > med	0.498	0.500	22779	0.508	0.500	21208	0.359	0.480	1571	$0.149^{\dagger\dagger\dagger}$	0.017

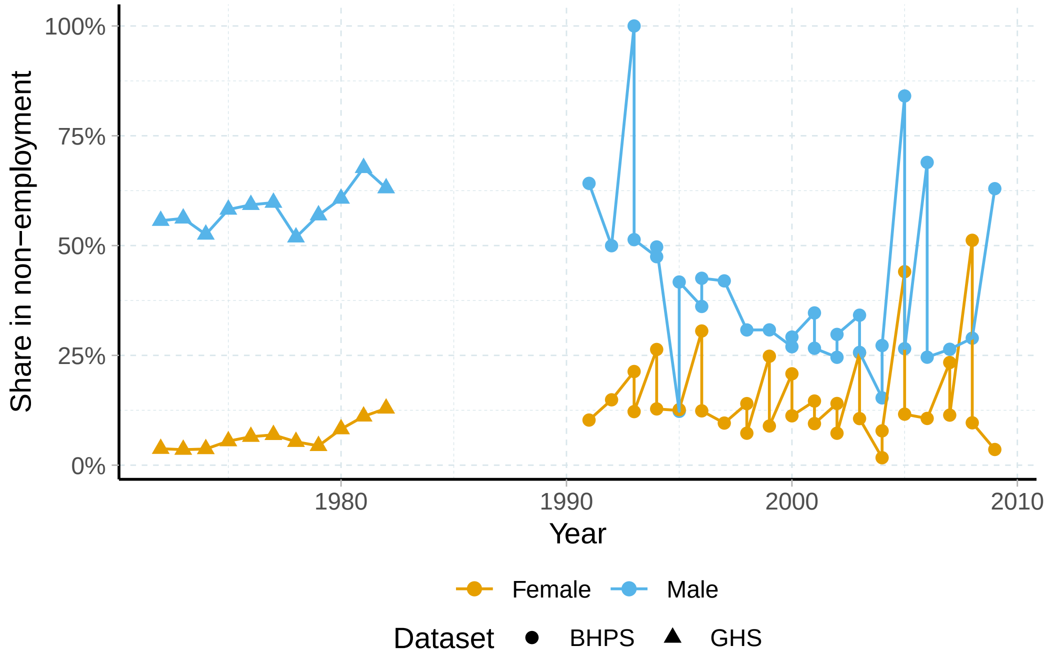
$^{\dagger}p < 0.1$; $^{\dagger\dagger}p < 0.05$; $^{\dagger\dagger\dagger}p < 0.01$ based on FDR adjusted p-values

Note: The table reports descriptive statistics in the working dataset before and after removing observations with missing intelligence score. Starting from the wave 3 of the UKHLS with 49 692 individuals, I restrict the sample to individuals who had non-zero sample weight, were born in the UK, were born between 1950 and 1995, finished school, complied with compulsory schooling laws, were not institutionalised at age 14, had non-missing highest educational qualification information, had non-missing intelligence score. The first three columns of the table (full sample) reports the descriptive statistics for this sample, i.e., before removing individuals with missing cognitive test results. The second three columns (non-missing intelligence) report descriptive statistics for the analysis with non-missing cognitive test results. The next three columns (missing intelligence) report descriptive statistics among removed observations with missing cognitive scores. The last two columns report difference in means between observations with missing and non-missing cognitive scores along with standard error of the difference. The significance stars of the difference in mean statistic are based on p-values adjusted for multiple inference (Benjamini and Hochberg 1995).



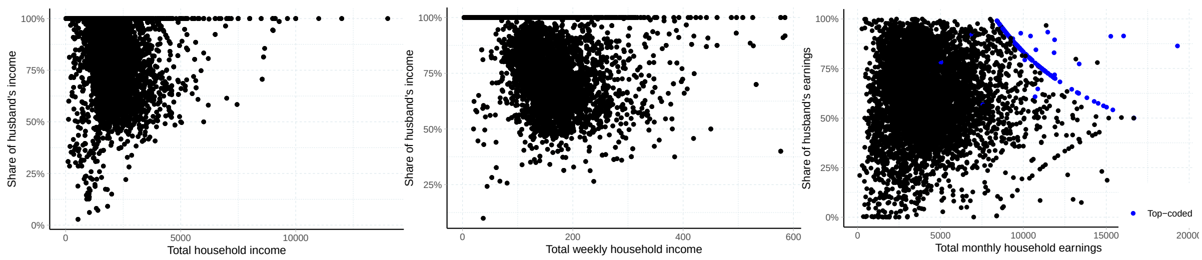
Note: The figure plots distribution of UKHLS working sample by status of each parent. The counts are weighted by cross-sectional response weights.

Figure G.1: Parental status at age 14



Note: The figure plots share of unemployed people seeking for work among all non-employed individuals aged between 40 and 50. The shares are unweighted in the GHS and weighted with cross-sectional weights from corresponding waves in the BHPS.

Figure G.2: Share of unemployed in non-employment at ages 40-50



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

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

Figure G.3: Distribution of household income

Table G.2: Heckman selection correction for realised labour-market outcomes

	Dependent variables			
	IHS earnings	IHS hourly wage	Hours	Log current job rank
Parent nonemp	-0.270***	-0.037***	-1.539***	-0.060***
	(0.064)	(0.009)	(0.431)	(0.013)
IQ	0.290***	0.046***	0.526**	0.104***
	(0.036)	(0.005)	(0.252)	(0.007)
Parent nonemp × IQ	0.122**	0.010	0.697*	0.020
	(0.061)	(0.009)	(0.410)	(0.013)
Obs.	20 307	20 307	20 307	20 307

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

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

Subsection G.1 Litareture summary

Table G.3: Literature summary

Paper	Identification strategy	Dataset	Result	Heterogeneity
Mörk, Sjögren, and Svaleryd (2019)	Propensity score matching	Swedish population-wide micro regster data 1987-2010	Childhood health, educational and early adult outcomes are not adversely affected by parental job loss	
Angelini, Bertoni, and Corazzini (2018)	Value-added models of personality	German Socio-Economic Panel Study (SOEP)	Parental unemployment makes offspring significantly more conscientious and - to smaller extent - less neurotic.	age at event, gender of child, gender of parent, parental educational, length of paternal unemployment
Hilger (2016)	Difference-in-differences	Federal tax returns 1996-2009	Layoffs only slightly redice college enrollment, college quality, and early career earnings.	family income, wealth, gender
Peter (2016)	Propensity score matching	German Socio-Economic Panel Study (SOEP)	Maternal job loss increases preschool children's socio-behavioural problems and decreases adolescents' belief in self-determination.	

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Table G.3: Literature summary (Continued)

Pan and Ost (2014)	Conditional Independence Assumption	Panel Study of Income Dynamics (PSID)	Parental job loss decreases college enrollment by 10 pp.	parental education, home ownership, family income, magnitude of income shock, unemployment benefit generosity, tuition fees
Brand and Thomas (2014)	Propensity score matching	National Longitudinal Survey of Youth (NLSY) and National Longitudinal Survey's Child-Mother file (NLSCM)	Significant negative effect of job displacement among single mothers on children's educational attainment and social-psychological well-being in young adulthood. Effects are concentrated among older children and children whose mothers had a low likelihood of displacement.	age at event, propensity for displacement
Coelli (2011)	Conditional Independence Assumption	Canadian Survey of Labour and Income Dynamics (SLID)	Significant negative effect of parental job loss on any post-secondary education enrollment, lowering the probability by 10.5pp.	parental education, income, age at event, local unemployment rate, university tuition fees

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Table G.3: Literature summary (Continued)

Rege, Telle, and Votruba (2011)	Conditional Independence Assumption	Norwegian registry matched with student registry 2003-2007	Negative effect of paternal job loss on children's school performance, but non-significant positive effect from maternal job loss.	age at event, local economy, gender
Stevens and Schaller (2011)	Fixed effects	US Survey of Income and Program Participation (SIPP)	Parental job loss increases the probability of children's grade retention by 0.8 percentage points, or around 15%.	family income, parental education, family composition
Akee et al. (2010)	Difference-in-differences	The Great Smoky Mountains Study of Youth (GSMS)	Increase in years of education by age 21 and decrease in criminality. The effects are largest in initially poor households. Potential mechanism is improvement in parent-child interactions.	gender of parent receing income boost, pre-treatment family income
Page, Stevens, and Lindo (2009)	Conditional Independence Assumption	Panel Study of Income Dynamics (PSID)	No evidence that firm closings have intergenerational effects on average, but found long-term costs on disadvantaged children.	family income, age at event

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Table G.3: Literature summary (Continued)

Oreopoulos, Page, and Stevens (2008)	Conditional Independence Assumption	Canadian Intergenerational Income Database (IID)	Children whose fathers were displaced have annual earnings about 9% lower. They are also more likely to receive unemployment insurance and social assistance. The estimates are driven by the experiences of children at the bottom of the income distribution.	pre-displacement income
Bratberg, Nilsen, and Vaage (2008)	Conditional Independence Assumption	Norwegian full population database of matched employer-employee data	No significant effects on earnings of children with fathers that experienced job loss.	pre-displacement income, father's education, industry

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