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The Effects of Parental Unemployment on Educational Attainment: A Within-Sibling Age Difference Approach

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Abstract

This paper utilises variation in siblings' age differences to identify the effects of parental unemployment on children's skills formation, using data from the Panel Study of Income Dynamics survey for US families from 1979 to 2019. More specifically, I use a within-family fixed effects approach to estimate the effects of time under parental unemployment on educational attainment, whether the effects are sensitive to the stages of childhood and whether they differ between highly and low-educated families. The findings show: (*i*) parental unemployment does not affect the probability of college attendance, and (*ii*) an additional year under highly educated fathers' unemployment reduces children's completed years of schooling, with the most substantial effects for children below or around the compulsory schooling starting age. Robustness testing reveals that the findings are robust to adjustments in age intervals and to reverse causality caused by children's health and the presence of newborns in the family.

Keywords: Unemployment, Schooling, Intergenerational Links, Skills Formation

Contents

1. Introduction

Parents can affect how children develop their skills through parental investments and choice of family environments (Cunha & Heckman, 2007). Therefore, adverse economic shocks could persist to future generations if parental unemployment negatively affects children's skills formation. This paper empirically analyses the relationship between parental unemployment and children's educational attainment because educational attainment provides a proxy for the knowledge and skills needed for individuals to effectively participate in the economy and society and, therefore, matters for the stock of human capital available in the labour force (OECD, 2010).

It is crucial to fully understand how children's educational attainment is affected by parental unemployment to develop policies to mitigate unemployment's effects on the future stock of human capital. Related empirical studies show that the impact of parental job losses (Bratberg et al., 2008; Oreopoulos et al., 2008; Stevens & Schaller, 2011) and income losses (Blau, 1999; Coelli, 2011; Lesner, 2018) on outcomes related children's skills, such as education and earnings, vary from no effects to negative effects. However, most of these studies focus either on the effects of parental job loss on children's income or parental income (changes) effects on children's earnings or education.

This paper uses a quantitative analysis to explain the relationship between parental unemployment and children's completed years of schooling and the probability of college attendance by using the Panel Study of Income Dynamics (PSID), a longitudinal household survey from the United States (US). The sample comprises 369 families with 871 children born between 1979 and 1994, where each child is observed from birth until at least age 25. An empirical strategy exploiting variation in siblings' age differences during parental unemployment is used to find how parental unemployment affects children's educational attainment. I find that one more year of parental unemployment does not affect the probability of children's college attendance and that paternal unemployment negatively affects children's completed years of schooling; however, only for children of highly educated fathers. Furthermore, younger children are more vulnerable to the effects of paternal unemployment.

This paper enhances the understanding of the intergenerational impact of unemployment in the US context. It identifies the vulnerable childhood periods affected by parental unemployment, examines the contribution of parents' education to these effects, and evaluates the differential effects of paternal and maternal unemployment. Additionally, the paper provides a framework for future research to explore the potential mechanisms through which parental unemployment affects children's skill development.

The rest of the paper is structured as follows. Chapter 2 delves into the existing literature on the topic; Chapter 3 describes the data and the sample; Chapter 4 explains the empirical methods used for the analysis; Chapter 5 presents the results; and Chapter 6 discusses the possible policy implications and concludes the paper.

2. Literature Review

2.1. Relevant Theories

Economic theories can help explain how parental unemployment may affect children's skills formation by affecting children's cognitive and non-cognitive skills. Both cognitive and non-cognitive skills allow individuals to increase their human capital according to Heckman, 2000 and Cunha and Heckman, 2007, who define cognitive skills as characteristics such as IQ and non-cognitive skills as characteristics such as social skills, self-discipline, patience, temperament, risk aversion, and time preference. This section shows how human capital theories explain genes, parental investments in children and family environments to determine children's skills and how the latter two explanations may be affected by parental unemployment.

According to the theory of inequality and intergenerational mobility by Becker and Tomes, 1979, parents maximise their utility by choosing the optimal investments (in the human capital and nonhuman capital) of their children and their own consumption based on expectations of how investments in children produce family income. Not only parent's investments but also the inheritability of parents' endowments, genes, and family environments (e.g., family reputation, connections, and knowledge) affect children's future income. Becker and Tomes, 1986 extend the theory by developing a model of transmission of earnings, assets, and consumption, where parents' utility depends on children's utility instead of their income. According to the model, already-possessed skills and family endowments raise the marginal effect of investment in human capital.

Heckman, 2000 proposes a theory where the rate of return on investment in human capital is higher for the highly skilled (similarly to Becker and Tomes, 1986) and for younger ages. He explains returns to human capital investments to be stronger for younger children because they have a longer horizon to recoup their benefits from investments and because 'skill begets skill'; early investment in skills promotes later investments. He has a strong emphasis that not only cognitive skills but also non-cognitive skills and motivation (that are also easier to alter in later life) are important in fostering human capital. Therefore, post-school learning and pre-school years from non-institutional environments and families are of vital importance for the future skills of the children.

Cunha and Heckman, 2007 introduced a model of skill formation that well summarises theories of Becker and Tomes, 1979, 1986 and Heckman, 2000. In the model of skill formation, families play a powerful role in shaping children's skills through genes, parental investments, and choice of child environments. According to the model, parents can affect children's preferences and drive the children towards the desired effort of parents by deciding on the inputs (investments and family environments) they put into the production of children's skills. The model suggests that there (i) is a transmission between cognitive and non-cognitive skills; emotionally nurturing environments support non-cognitive skill formation and cognitive skill formation indirectly as non-cognitive skills foster cognitive skills, and (ii) skills in younger ages increase the productivity of skill formation in later ages.

The aforementioned models can be used to predict how parental unemployment can play a role in children's skills formation, as (*i*) unemployment lowers family income that can be used to invest in children's skills, and (*ii*) unemployment can worsen family environments, harming non-cognitive skill (and therefore also cognitive skills). However, it is important to note that investments in children, family environments and genes may be correlated with families' tendency to be unemployed since parents who get unemployed may be endowed with lower skills, worse reputations, and less nurturing emotional environments.

2.2. Empirical Findings

The literature matrix in Table 2.1 summarises the most relevant empirical studies on parental unemployment and parental income's effect on children's skills. I chose the literature based on two criteria: first, the use of variables related to parental unemployment or income as explanatory variables since these two measures work as proxies for change in parental investments and family environments. Second, the use of children's labour market or educational outcomes as dependent variables since they work as a proxy for children's skills. The literature generally points towards parental income or job loss to negatively affect their children's income and earnings, although the effects vary between countries. The findings show that the effects are often driven by low-income families and by permanent rather than current changes in income. A common limitation in the studies is causal identification, as unemployment and income are endogenously determined by unobserved family characteristics. To tackle this issue, the literature often uses instrumental variable and fixed effects models as their identification strategy.

A commonly used identification method uses within-family fixed effects, such as within-sibling estimators, to control for time-invariant unobserved family characteristics. Permanent components of family characteristics such as income, skills, or endowments will, if uncontrolled, bias the results of how parental income changes or job losses affect children's outcomes. The studies show parental income to be negatively related to children's outcomes: Blau, 1999 estimates parental income's effect on children's human capital stock by using within mother's siblings, within-siblings and within-child fixed effects and finds parents' permanent income to be more important for child development than parents' current income; Levy, Duncan et al., 2000 use within-sibling effects and show that a $10,000 increase in average annual family income during the early childhood ages leads to an increase of 0.11-0.16 years of completed schooling; Lesner, 2018 uses within-child fixed effects and finds one additional year of childhood poverty to reduce future disposable income by 2.2% and years of schooling by 8.1%. However, studies on job losses do not find similar long-run effects as with income; Bratberg et al., 2008 find fathers' displacement to have no effects on children's earnings; Stevens and Schaller, 2011 use within-child fixed effects and find parental job loss in the prior year to increase the probability of children's grade retention by 15%.

Another set of methodologies to address the endogeneity problems uses two-stage least squares (2SLS) models, such as the instrumental variable (IV) model. Dahl and Lochner, 2012 use income tax credit changes as an instrument for family income and show $1,000 increase in income to increase combined math and reading test scores by 6% of SD in the SR and that

Table 2.1

Summary of Empirical Findings on the Effects of Parental Income or Parental Job Loss on Children's Outcomes

Study	Main Research Subject	Data	Methodology	Main Results
(Lesner, 2018) (Journal of Population Economics)	The effect of childhood poverty on later life labour and marriage market outcomes.	Danish administrative data, IDA. Children born 1980-83. Observed 2008-2011. A sample of 32,357 children and their parents	FE within-sibling	An additional year of childhood poverty between ages 0 and 21 → disposable income -2.2%. → years of schooling -8.1%
(Dahl & Lochner, 2012) (American Economic Review)	The effect of shocks on family income on low-income families' children's education achievement	the US. NLSY. Sample of 4,412 children of 2,401 mothers affected 1988-2000	IV Earned Income Tax Credit changes used for family income	$1,000 increase in income → combined math and reading test scores + 6 % of standard deviation in the short run.
(Stevens & Schaller, 2011) (Economics of Education Review)	The effect of parental job loss on children's next year's academic achievement	SIPP. The US. 2,170 children between 1996-2004	FE within-child	Job loss in the prior year → probability of children's grade retention +15%
(Coelli, 2011) (Journal of Labor Economics)	The effect of parental job loss on child's enrolment for post-secondary institution or university.	Canada. SLID. 2,403 youth and their parents affected 1993-2007	LPM	$1,000 decline in income when a child completes high school → 1pp reduction in university enrolment
(Oreopoulos et al., 2008) (Journal of Labor Economics)	The effect of father's job loss on sons' annual earnings	Canadian administrative data. Job displacements 1978-1999. 1,411 affected children.	FE & IV Three-way interaction between the Shock variable, region, and initial industry for post-displacement income	Father's displacement due to plant closing: → sons' labour earnings -9% The findings are driven by bottom-income families
(Bratberg et al., 2008) (Journal of Labor Economics)	The effect of family resources on children's economic outcomes	Norwegian population database of matched employer-employee data. 720 affected fathers 1986-1987	FE	Fathers' displacement has no effects on children's earnings
(Shea, 2000) (Journal of Public Economics)	The effect of parents' income on children's human capital	The US. PSID. 1,669 children and 783 fathers affected 1968-1989.	2SLS union status, industry, and job loss for income variation	Parent's income variation has an insignificant effect on the child's wages, earnings, income, and education
(Levy, Duncan et al., 2000) (Joint Center for Poverty Research)	The effect of family income on children's completed years of schooling	the US. PSID. 863 children in 391 families affected 1968-1976.	FE within-sibling	$10,000 increase in average annual family income during child aged 0-4 → +0.11-0.16 years of completed schooling
(Blau, 1999) (The Review of Economics and Statistics)	The effect of parental income on the human capital stock of young children	the US. NLSY. 8,513 children of 4,180 mothers affected 1979-1991.	FE & RE within-mother's sibling, sibling, and child	Current income's effect on child development is small. Permanent income's effect on child development is larger.

Notes. NLSY, National Longitudinal Survey of Youth. SLID, Survey of Labour and Income Dynamics. SIPP, Survey of Income and Program Participation. IDA, Integrated Database for Labour Market Research. OLS, ordinary least squares. FE, fixed effects. RE, random effects. 2SLS, two-stage least squares. IV, instrumental variable. LPM, Linear probability model long-run average income affects test scores more than current income, while Shea, 2000 uses 2SLS estimation using union status, industry and job loss for income variation and finds the parent's income variation to have an insignificant effect on the child's wages, earnings, income and education.

Few papers rely on different methodologies. Coelli, 2011 uses a linear probability model for parental job loss and finds $1000 decline in income around the time when a child completes high school to reduce university enrolment by one percentage point. Oreopoulos et al., 2008 use a combination of methodologies and estimate the effect of a shock of a father's plant closing on sons' labour earnings, finding a negative effect of 9% and that bottom-income families drive the effects. Oreopoulos et al., 2008 include individual fixed effects for fathers and an instrumental variable for addressing endogeneity in post-displacement income.

2.3. Hypotheses

Human capital theories suggest that children's skills formation is shaped by parental investments and family environments, both of which can be related to parental unemployment. To investigate the intergenerational relationship between unemployment and skills formation, this paper focuses on how parental unemployment affects children's educational attainment. My approach is inspired by Lesner, 2018 and Levy, Duncan et al., 2000, who use within-sibling fixed effects and utilise siblings' age variation in their identification method, both of which use family income variation instead of parental unemployment as an explanatory variable. Based on human capital theories and empirical findings related to unemployment's or income's effects on children's outcomes, I expect (*i*) the time under parental unemployment to reduce children's completed years of schooling and probability of college attendance[1]; (*ii*) parental unemployment's effects on children's completed years of schooling and probability of college attendance to be stronger in low-educated families[2]; and (*iii*) parental unemployment's effects on children's completed years of schooling and probability of college attendance to be stronger for younger ages[3][4].

3. Data

This paper uses a quantitative analysis to explain the relationship between parental unemployment and children's skills formation, measured in completed years of schooling and the probability of college attendance, using the Panel Study of Income Dynamics (PSID). This

[1] Theoretical prediction: parental investments and choice of child environments shape children's skills (Cunha & Heckman, 2007). Empirical finding: one additional year of childhood poverty decreases children's years of schooling (Lesner, 2018).

[2] Theoretical prediction: parental skills increase the rate of return of parental investments in children (Cunha & Heckman, 2007). Empirical findings: father's job loss reduces sons' annual earnings more in low-income families (Oreopoulos et al., 2008) and income increases raise children's test scores more for children from disadvantaged families (Dahl & Lochner, 2012).

[3] Theoretical prediction: the rate of return for investments in human capital is higher for younger ages (Heckman, 2000). Empirical finding: The negative effect of one additional year of poverty during childhood on years of schooling is higher for older children (Lesner, 2018).

[4] I expect a stronger effect for younger ages although the theoretical predictions and empirical findings here are somewhat conflicting.

chapter describes the data source, sample selection, descriptive statistics, variables, and context and data trends.

3.1. Data Source

The data is retrieved from PSID, a longitudinal household survey from 1968 until 2022, following more than 18,000 individuals from 5,000 families in the United States. An advantage of PSID is that besides following individuals of included families, it follows the new families or households of children after they split off from their original families. Furthermore, PSID allows the identification of family relations. The PSID sample consists of an original 1968 sample of families that oversampled low-income families, refresher samples from 1997 and 2017, and the descendants of families and their new families. A limitation of the data is that a reference person, *the head of the family*, fills in the survey for the whole household. Therefore, cross-validation between father and mother is not possible. I extracted the following information from the database: demographic information such as age, family relations, marriage status, gender and changes in family composition, parents and children's completed years of schooling, college attendance, parents' employment status[1] and children's health status and birth weight.

3.2. Sample Selection

I restricted my sample to biological two-parent families[2] with at least two children born between 1979 and 1994 and who continued to follow the survey at least until the age of 25 and at least one of which has experienced parental unemployment between ages zero and 16. The data consists of 29 observations per child as parental employment status is surveyed annually from 1979 to 1997 and biennially from 1997 until 2019[3]. All siblings and parents were linked with family and sibling identification numbers. I excluded individuals who did not report completed years of schooling or whose completed years differed for more than four years of within-family average. My final sample consists of 369 families with 871 children.

3.3. Variables

Using socioeconomic data from the PSID dataset, I constructed the variables presented in Table 3.1[4]. *Schooling* and *College* are the dependent variables representing a child's acquired skills, where *Schooling* is the child's highest grade completed or the highest completed year of schooling and takes a value of 16 if a person is at least a college graduate and a value of 17 if a person has completed at least some postgraduate work. *College* is a binary variable for whether a child attended at least some college. *Schooling* is measured at or the closest available year after age 25, while *College* is measured as reported in 2019 due to lack of data availability. The explanatory variables of interest include *Years Unemployed* and *Parent Schooling High*

[1] I would also have included parental income but too high missingness of the data prevented me from including both employment status and income without significantly reducing the statistical power of my analyses

[2] I allowed families not to be intact and changes in family composition.

[3] Employment data starts from the year 1979 and children born in 1994 or before are at least of age 25 at the end of 2019.

[4] Correlations between variables are presented in Figure A.2 in the Appendix

(and *Father Ever Unemployed*). *Years Unemployed* is the number of years a child experienced paternal or maternal unemployment at a given age interval. A parent is considered unemployed when they report being laid off or unemployed and looking for work as their employment status[5]. *Parent Schooling High*, a binary variable for whether parents have a mean completed years of schooling of 13 or more[6][7] represents whether a child is from a highly educated family.

A set of control variables were included in some of the regressions. Those variables, found in Table 3.1, give information about parents' schooling, demographics, family structure and its changes and employment statuses other than unemployed or employed. The employment status variable retrieved from the PSID is a categorical variable taking different values if a person is working, unemployed, disabled, retired, etc. Therefore, I set employment statuses other than unemployed or employed to zero in the *Years Unemployed* variable and construct a new *Years* variable for each to control for omitted variable bias. Moreover, if one or more variables or interests are endogenous of control variables, including the controls biases the estimates. Therefore, some of the analyses are run with and without controls.

3.4. Descriptive Statistics

Table 3.2 provides descriptive statistics for child-specific variables for the sample of highly-educated and low-educated families and the total sample. Variables in the table are measured per child. The table shows that the number of children whose parents are described as highly educated takes up 45.0% (394 individuals) of the sample of 871 children. The mean schooling, college attendance, parental schooling, born into an intact family and mother's age at birth are higher, and the number of years under parental unemployment, father ever experiencing unemployment and the number of years of unreported employment status are lower for children of highly educated parents than of low-educated parents as one might expect. Furthermore, there are no significant differences in the birth years and sex of children between the two groups.

Table 3.3 showcases how families with a higher likelihood of experiencing unemployment differ in their unobserved characteristics (e.g., genes and inheritability of endowments). Only one family in the sample never experienced paternal or maternal unemployment when any of their children were between zero and 16 years old, and therefore, I split the descriptive statistics to families whose fathers did not (*Father Never Unemployed*) and to families whose fathers did (*Father Ever Unemployed*) report any unemployment in that age interval. The mean of schooling, college attendance and parental schooling are higher for children from families that have never experienced paternal unemployment. However, the differences between the two groups are not as large as between highly and low-educated families. The table hints that families who differ in their unemployment experiences produce less educated children and are inherently different in their characteristics, motivating the use of family fixed effects in estimating parental unemployment's effects on children's educational attainment. Furthermore, families who report their fathers ever experiencing unemployment have more missing years of reported employment

[5]Layoffs included in the unemployment variable to increase the statistical power of the estimates. The robustness of the unemployment variable with regards to the inclusion of layoffs is assessed in Section 5.4.5

[6]The relatively low value of 13 years chosen to avoid reducing the statistical power of the highly educated group.

[7]See section 3.5 for more details about education in the US

Table 3.1

Variable Descriptions

Variables of Interest	Description
Schooling	The number of completed years of schooling of a child: the highest grade or year of school completed
College	A binary variable for whether a child attended college
Father Ever Unemployed[a]	A binary variable for whether a father ever experienced unemployment when any child in the family was between zero and 16
Years Unemployed[bc]	The number of years a child experienced paternal or maternal unemployment at a given age interval
Parent Schooling High[b]	A binary variable for whether parents' average completed years of schooling is 13 or higher[d]
Control Variables	
Parent Schooling[b]	The parents' average completed years of schooling
Years Retired[bc]	The number of years a child's mother or father was retired at a given age interval of a child
Years Disabled[bc]	The number of years when a child's mother or father was disabled at a given age interval of a child
Years Housewife[bc]	The number of years when a child's mother or father was keeping home at a given age interval of a child
Years Student[bc]	The number of years when a child's mother or father was a student at a given age interval of a child
Years Missing[bc]	The number of years when a child's mother nor father reported their employment status at a given age interval of a child
Parent Divorced[c]	A binary variable for whether a child's parents divorced or a parent moved out of the household at a given age interval of a child
Parent Died[c]	A binary variable for whether a child's parent died at a given age interval of a child
Intact Family	A binary variable for whether a child was born into an intact family
Sex	A binary variable whether a child is a male
Birth Order	The ordinal position of a child among siblings
Birth Year	The scaled year of birth of a child
Mother Age at Birth	The age of a mother when the child was born
Number of Children	The number of children in the family
Birth Weight[e]	The weight of a child at birth in ounces
Years Bad Health[ef]	The number of years when a child was reported to be in bad physical health at a given age interval

Notes. Variable descriptions of the variables of interest and the control variables. [a] The variable is included only in the OLS model. [b] The variable is evaluated per both parents, father or mother, depending on the model specification: father and mother-specific information is used in heterogeneity analyses. [c] The variable is evaluated per age interval specified by each model specification. [d] If only one parent reported their completed years of schooling, then their schooling was assigned as the average schooling. [e] The variable is only used in robustness test in Section 5.4.4. [f] Footnote 7 explains the construction of the variable in more detail.

Table 3.2

Descriptive Statistics for Child-specific Variables for Sample of High-Educated Families, Low-Educated Families and the Total Sample

	Schooling High		Schooling Low		Total			
	Mean	SD	Mean	SD	Mean	SD	Min	Max
Schooling	14.39	1.98	12.81	1.94	13.52	2.11	5	17
College	0.85	0.36	0.56	0.50	0.69	0.46	0	1
Years Unemployed								
Ages 0-16	1.70	1.79	2.33	2.22	2.05	2.06	0	14
Ages 0-4	0.59	0.84	0.68	0.97	0.64	0.91	0	4
Ages 5-9	0.59	0.89	0.84	1.08	0.73	1.00	0	5
Ages 10-16	0.52	0.87	0.81	1.01	0.68	0.96	0	6
Father Ever Unemployed	0.43	0.50	0.63	0.48	0.54	0.50	0	1
Years Retired	0.04	0.20	0.03	0.23	0.03	0.22	0	3
Years Disabled	0.19	0.80	0.58	1.92	0.41	1.53	0	14
Years Housewife	2.73	3.10	3.36	3.48	3.08	3.32	0	14
Years Student	0.44	0.99	0.25	0.65	0.34	0.83	0	6
Years Missing	0.72	2.20	1.63	3.30	1.22	2.89	0	16
Parent Schooling	14.60	1.25	11.02	2.07	12.62	2.50	2	17
Birth Year	1987.17	3.84	1986.95	3.95	1987.05	3.90	1979	1994
Sex	0.51	0.50	0.44	0.50	0.47	0.50	0	1
Intact Family	0.77	0.42	0.56	0.50	0.66	0.48	0	1
Parent Divorced	0.01	0.07	0.00	0.00	0.00	0.05	0	1
Parent Died	0.02	0.12	0.00	0.06	0.01	0.10	0	1
Mother Age at Birth	27.43	4.98	24.87	4.67	26.03	4.98	15	41
Number of Children	2.50	0.73	2.57	0.75	2.54	0.74	2	5
N Individuals	392		479		871			
N Observations	10320		15960		26280			

Notes. The table describes the means, standard deviations (SD) and value ranges of variables defined in Table 3.1 for children from highly-educated families, low-educated families and the total sample. *Years Unemployed* variable shows the number of years under paternal or maternal unemployment. Each *Years* variable follows the same logic. N Individuals is the number of unique children.

status, suggesting that unemployment in the data may be selectively underreported[8].

3.5. Trends

This section describes the educational context and the unemployment trends in the United States, illustrates the relationships between parental unemployment and children's educational attainment in the sample and finally, explains the possible issue of selective attrition in the data. Understanding the educational context of the US for children born between 1979 and 1994 is important for drawing any conclusions related to educational attainment. The compulsory education laws in the US differ across states, increasing the difficulty of distinguishing voluntary schooling from involuntary schooling. According to the National Center for Educational Statistics (NCES, 2020), in 2017, compulsory education in the US started between ages five and seven and ended between ages 16 and 18. The lowest number of years of required schooling attendance in a state was nine years, and the highest was 13. Table A.3 and Figure A.1 shows the mandatory schooling per each (available) state in 2017 and the density of completed years of schooling in the sample, respectively. The pattern in Figure A.1 reveals that *Schooling* is double-peaked;

[8] I discuss this issue regarding selective attrition and measurement error in Sections 3.6 and 4.2, respectively.

Table 3.3

Descriptive Statistics for Child-specific Variables for Sample of Families Whose Fathers Never Experienced Unemployment, Whose Fathers Experienced Unemployment and the Total Sample

	Father Never Unemployed		Father Ever Unemployed		Total	
	Mean	SD	Mean	SD	Mean	SD
Schooling	13.77	2.21	13.31	2.00	13.52	2.11
College	0.72	0.45	0.67	0.47	0.69	0.46
Years Unemployed						
Ages 0-16	1.47	1.57	2.54	2.29	2.05	2.06
Ages 0-4	0.49	0.76	0.77	1.01	0.64	0.91
Ages 5-9	0.53	0.83	0.90	1.10	0.73	1.00
Ages 10-16	0.45	0.76	0.88	1.06	0.68	0.96
Years Retired	0.03	0.26	0.03	0.18	0.03	0.22
Years Disabled	0.29	1.07	0.50	1.84	0.41	1.53
Years Housewife	2.72	3.11	3.39	3.47	3.08	3.32
Years Student	0.39	0.92	0.29	0.73	0.34	0.83
Years Missing	1.10	2.78	1.32	2.98	1.22	2.89
Parent Schooling	13.05	2.48	12.26	2.46	12.62	2.50
Birth Year	1987.30	3.79	1986.83	3.98	1987.05	3.90
Sex	0.47	0.50	0.48	0.50	0.47	0.50
Intact Family	0.59	0.49	0.72	0.45	0.66	0.48
Parent Divorced	0.00	0.07	0.00	0.00	0.00	0.05
Parent Died	0.01	0.10	0.01	0.09	0.01	0.10
Mother Age at Birth	26.08	5.22	25.98	4.76	26.03	4.98
Number of Children	2.42	0.64	2.64	0.81	2.54	0.74
N Individuals	401		470		871	
N Observations	12090		14190		26280	

Notes. The table describes the means and standard deviations (SD) of variables defined in Table 3.1 for children from families whose fathers did not report any unemployment when their children were between zero and 16 years old (*Father Never Unemployed*), for families whose fathers did report unemployment when their children were between zero and 16 years old (*Father Ever Unemployed*) and the total sample. *Years Unemployed* variable shows the number of years under paternal or maternal unemployment. Each *Years* variable follows the same logic. N Individuals is the number of unique children.

most children end their schooling after year 12, while the second most common time to finish schooling is after obtaining a college degree with no postgraduate work (year 16). Furthermore, the distribution of completed schooling reveals non-normality in the *Schooling* variable.

Whether the sample is representative of the US population matters for the generalisability of results. Figure 3.1 illustrates the relationship of the sample and the US population regarding unemployment rates. More specifically, the figure shows the annual unemployment rates in the US reported by the OECD, in the sample, and of variable *Years Unemployed*. The unemployment rate in the sample follows the trends reported by the OECD relatively closely, although the rates are higher, as expected, due to oversampling of low-income families. Moreover, the unemployment trend of *Years Unemployed* shows a similar, although more elevated and more volatile, pattern compared to the other two unemployment rates. The pattern, however, is expected due to the nature of the variable as it describes unemployment as at least one parent being unemployed. Based on Figure 3.1, There is no reason to expect the sample's unemployment rate to differ from that of the US population systematically.

Scatterplots in Figure 3.2 illustrate the relationship between children's completed years of schooling and years under parental (Row 1), paternal (Row 2) and maternal (Row 3) unemploy-

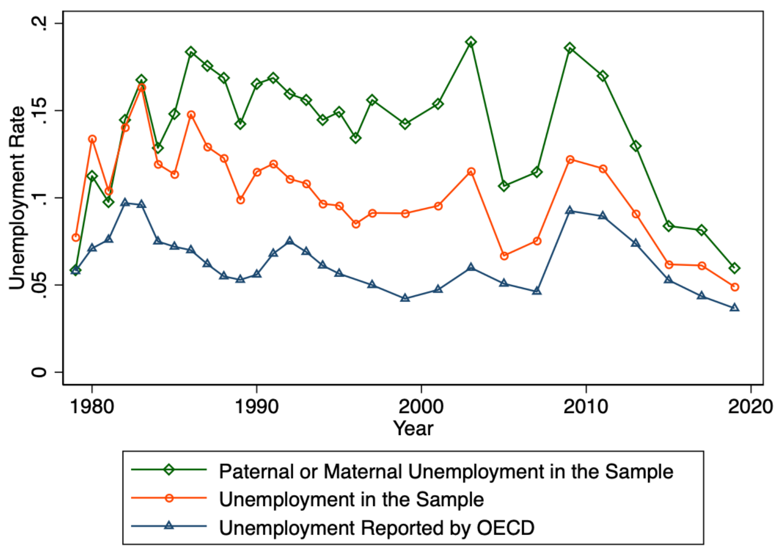

Figure 3.1. Unemployment rates in the Unemployment Variable, in the sample and in the United States Reported by OECD . The figure shows the unemployment rates in the unemployment variable *Years Unemployed* (green diamond), in the sample (red circle) and in the United States reported by The Organization for Economic Cooperation and Development (OECD) (blue triangle). *Data Sources.* Panel Study of Income Dynamics and OECD, 2023.

ment. The left column shows correlations for each child in the sample, and the right column shows within-family correlations. The trends in the left column show that children's completed years of schooling decline slightly with years under parental unemployment regardless of the unemployment measure used. On the other hand, in contrast to expectations, the right column shows a slight positive correlation between within-family years under unemployment and within-family completed years of schooling. However, unobserved within-family factors such as parents' student status or children's birth order can drive these positive correlations. Overall, the trends in Figure 3.2 reveal that correlations between years under parental unemployment and schooling depend on with whom the comparisons are made and motivates using within-families analysis to identify unemployment's effects on educational attainment.

3.6. Selective Attrition

A problem arises with the explanatory variable of interest, the number of years a child experienced parental unemployment at a given age interval if unreported employment status contains information driving children's educational attainment. The observable data on parental unemployment suffers from selective attrition if the respondents are more likely not to respond to a question about their employment status if they are unemployed. This selective missingness of employment data would bias unemployment's estimated effects downwards. Out of the total number of observations, 15.1% are cases where neither father nor mother reports their employment status, whereas the same rate is 36.0% and 22.9% for fathers' and mothers', respectively.

To evaluate whether selective attrition occurs in reporting unemployment, I run probit regressions (Table A.18 in the Appendix) to identify whether the characteristics of the unemployed match the characteristics of those who are missing responses for employment status. The probit regressions show similarity in how some parental characteristics help predict unemployment and

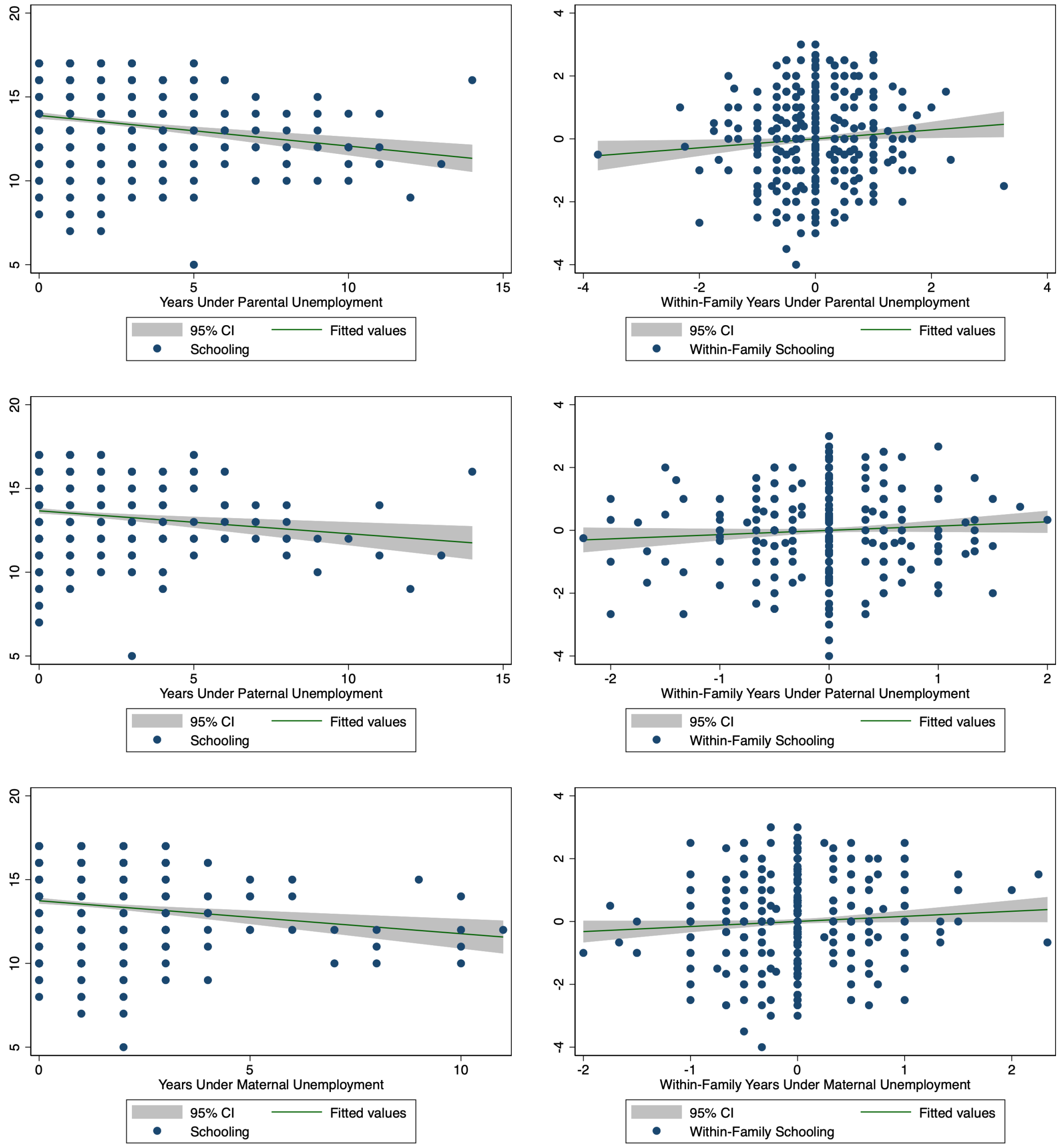

Figure 3.2. Scatterplots of Correlations between Completed Years of Schooling and Years Under Parental Unemployment During Ages Zero to 16. The figure shows scatterplots of completed years of schooling (*Schooling*) and years under parental unemployment. The left column shows scatterplots for each child in the sample, and the right column shows scatterplots for within-family completed years of schooling and within-family years under parental unemployment. The scatterplots use paternal or maternal, paternal, and maternal unemployment on the x-axis in Rows one, two and three, respectively. Years under unemployment are measured between age interval zero to 16. CI, confidence interval. *Data Source.* Panel Study of Income Dynamics.

non-response. Parents who are lower-educated or are not married or cohabiting are more likely to be unemployed or non-respondents. However, the unemployed's and non-respondents' ages predict opposite outcomes. Nevertheless, based on the probit analyses, the possibility that the unemployed are more likely to not respond to employment status compared to the rest of the population cannot be excluded. A control variable for missing years of reporting employment[9] is used to tackle this possible issue.

4. Empirical Strategy

The empirical strategy of this paper exploits the variation in sibling age differences during parental unemployment to find how parental unemployment affects children's completed years of schooling and the probability of college attendance[1]. First, I showcase how family-fixed characteristics, such as parental education level, drive the association between parental unemployment and children's educational attainment by using an ordinary least squares (OLS) model. Secondly, I use the family fixed effects (FE) model to find parental unemployment's effect on children's educational attainment. Thirdly, I discuss whether the identifying assumptions for fixed effects estimations are met.

4.1. The Models

A simple OLS regression is used to estimate how one more year under parental unemployment is associated with children's completed years of schooling or the probability of college attendance and whether the association is dependent on children's age as follows:

$$Y_{i,f} = \beta_0 + \sum_{j=1}^{s} \beta_j Unemp_{i,f} + \boldsymbol{X}_{i,f}\beta + \alpha_f + u_{i,f}. \tag{4.1}$$

In Equation 4.1, Y is the dependent variable: completed years of schooling or the probability of college attendance of child i from family f. Subscript j represents the age intervals, and s assigns the number of age intervals used by taking the value of one when an age interval from zero to 16 is used and the value of three when age intervals from zero to four, five to nine and 10 to 16 are used. *Unemp* represents *Years Unemployment*, the number of years of parental unemployment a child experienced at a given age interval that is the explanatory variable of interest. $\boldsymbol{X}\beta$ is a set of control variables described in Table 3.1[2]. The total error consists of two components: the sibling or time-variant idiosyncratic component u[3] and the family fixed effects (Sibling or time-

[9]See *Years Missing* in Table 3.1

[1]I use linear probabilities in the case of college attendance

[2]The set of control variables is of form:

$$\boldsymbol{X}_{i,f}\beta = \beta_{s+1}\boldsymbol{X}_{i,f,1} + \beta_{s+2}\boldsymbol{X}_{i,f,2} + ... + \beta_{s+K}\boldsymbol{X}_{i,f,K}, \tag{4.2}$$

where subscript K is the number of controls. However, the form changes slightly when interactions and fixed effects are added

[3]Sibling or time-variant because the idiosyncratic error may arise from sibling-specific characteristics or time-variant family characteristics.

invariant) component α[4]. I add additional model specifications with interaction between *Years Unemployment* and whether parents are highly educated (*High* representing variable *Parent Schooling High*), presented as follows:

$$\begin{aligned} Y_{i,f} &= \beta_0 + \sum_{j=1}^{s} \beta_j Unemp_{i,f} + \beta_{s+1} High_f \\ &+ \sum_{j=s}^{2s} \beta_j High_f \times Unemp_{i,f} + \boldsymbol{X}_{i,f}\beta + \alpha_f + u_{i,f}, \end{aligned} \tag{4.3}$$

to test whether there is a stronger correlation between parental unemployment and children's educational attainment in low-educated families.

The estimations of regressions presented in Equations 4.1 and 4.3 are biased because α is not measured and likely correlates with *Years Unemployment*. It is difficult to identify the family fixed effects component α well, and therefore, using a family fixed effects estimation by taking out within-sibling averages is a less biased method for evaluating unemployment's effect on children's educational attainment. Family fixed effects effectively drop sibling or time-invariant family characteristics out of the equation[5]. However, *Years Unemployment* survives the within-sibling subtraction only if siblings differ in their years under parental unemployment in a given age interval.

Following Lesner, 2018, I estimate parental unemployment's effects in two ways: (i) by pooling the years under parental unemployment in one age interval from ages zero to 16 and (ii) by pooling the years under parental unemployment into three age intervals, zero to four, five to nine and 10 to 16[6]. In addition, I split some of the control variables into corresponding age intervals (see Table 3.1 for more details.). Pooling unemployment into one or three age intervals instead of using each age separately increases the statistical power of the fixed effects estimates[7] and gives a more accurate estimation of parental unemployment's effects. Equations

$$\begin{aligned} &Y_{i,f} - Y_f \\ &= \sum_{j=1}^{s} \beta_j [Unemp_{i,f,j} - Unemp_{f,j}] + [\boldsymbol{X}_{i,f} - \boldsymbol{X}_f]\beta + [u_{i,f} - u_f], \end{aligned} \tag{4.4}$$

[4]If children born in different years would tend to differ in their education outcomes, for example, because they got exposed to recessions, then also birth-year fixed effects should be added in the regression. I use a joint F-test to test if all birth years jointly equal zero and conclude that birth-year fixed effects are not necessary.

[5]Fixed effects estimator is preferred over random effects estimator since time-invariant family characteristics are expected to be correlated with the regressors. The Hausman specification test confirms that using fixed effects is a more appropriate method.

[6]I choose pooling unemployment to age intervals over using the age of a child when they first experience parental unemployment to analyse sensitive periods of parental unemployment because of the nature of the unemployment data: unemployment spells tend to be short, scattered over children's childhood and missing years of employment status data may bias the estimates more if first experiences of parental unemployment is used.

[7]Age intervals are chosen based on two criteria: the intervals should represent different stages of childhood and have approximately equal number of children that have within-family variation in their experienced parental unemployment. Low statistical power in parental education level-specific estimates may be a concern. Tables A.1 and A.2 in the Appendix show the number of children with within-family variation in experienced parental unemployment for the whole sample and in highly educated families, respectively.

and

$$
\begin{aligned}
&Y_{i,f} - Y_f \\
&= \sum_{j=1}^{s} \beta_j [Unemp_{i,f,j} - Unemp_{f,j}] + \sum_{j=s}^{2s} \beta_j [High_f \times (Unemp_{i,f,j} - Unemp_{f,j})] \\
&+ [\boldsymbol{X}_{i,f} - \boldsymbol{X}_f]\beta + [u_{i,f} - u_f],
\end{aligned}
\tag{4.5}
$$

present the family fixed effects model with and without interaction with high parental schooling, respectively. In Equations 4.4 and 4.5, family averages presented with subscript f are subtracted, subscript j represents the age intervals, and s assigns whether one or three age intervals are used. The fixed effects equations are used to estimate how the difference between siblings' number of years under parental unemployment at a given age interval affects the difference in siblings' completed years of schooling or the probability of college attendance. This estimation method gives the marginal effect of one more year under parental unemployment. My empirical strategy is similar to Lesner, 2018 with a few changes. Firstly, Lesner uses years under childhood poverty instead of years under parental unemployment. Secondly, he uses a control group of siblings who are either not born yet or above the age of 21. However, due to more limited data availability, the empirical strategy in this paper has to rely on available variation in siblings' experiences of parental unemployment, where each sibling in the family may have been affected by parental unemployment.

4.2. Assumptions and Limitations

This section discusses how the family fixed effects model fits the assumptions for fixed effects estimation. The two main concerns in identifying assumptions are endogeneity and measurement error. First, for the exogeneity assumption to hold, the idiosyncratic error (u) should be exogenous of the timing and length of parental unemployment and unobserved time-invariant family characteristics for all children. The idiosyncratic error is not independent of employment status if a child's disability, health problem, or other problem requiring plenty of parental attention affects the parent's employment status or unemployment's timing or length. To address this reverse causality issue, I use additional information about children's birth weight, whether children are reported to be in poor health and whether a family has a newborn child in Section 5.4.4 to (i) control for children's characteristics that may reveal information about whether a parent chose to become or got unemployed due to reasons related to poor health or a disability of a child or to take care of a newborn child, and (ii) to exclude years under parental unemployment that have a high risk of reverse causality.

Besides the issue of reverse causality, endogeneity may be caused by omitted variable bias. If between-sibling variance arises because of differences in time-variant family characteristics, such as moving states and income changes, the estimates of unemployment's effects will be biased. Unfortunately, these time-variant family characteristics are not included in this paper's models due to a lack of data availability in (publicly available) PSID datasets.

Second, a measurement error in employment status caused by under-reporting unemployment would bias the estimated effects of unemployment towards zero. Unfortunately, cross-validation between father and mother is not possible as a reference person, *the head of the family*, fills in the PSID survey for the whole household. As in most cases, the father is assigned as the reference person, and self-reporting may lead to misreporting employment status; fathers' employment status may be especially vulnerable to measurement error. Past literature addresses measurement errors using two-stage least squares, instrumental variables or alternative measures of unemployment. However, the PSID data does provide alternative measures of unemployment with a sufficiently long timeframe. I attempt to use reductions in fathers' total taxable income as an alternative measure for unemployment; however, a significant amount of missing self-reported data leads the variable not to provide enough information about fathers' unemployment.

Another source of measurement error in the unemployment variable may occur due to the inclusion of temporary layoffs as unemployment. This paper considers a person to be unemployed if they report being *only temporarily laid-off* or *unemployed, looking for work* as their employment status. Temporary layoffs may not cause similar stress in the family environment or similar reductions in parental investments in children as unemployment, and therefore, bias the unemployment variable's effects towards zero. For example, laid-off parents may expect to return to work soon, or layoffs may be predictable due to the seasonal nature of work. I address this possible measurement error in Section 5.4.5 by splitting the unemployment variable into a layoff variable and an unemployment variable that excludes layoffs.

A few additional issues in fixed effects assumptions require attention. Modified Wald tests reveal heteroskedasticity in the fixed effect models, and interaction between siblings likely causes correlations between siblings' errors (because of sibling spillovers or compensating investment, see Lesner, 2018). For these reasons, I use within-family clustered standard errors in the fixed effects model. Lastly, non-normality in the completed years of schooling variable causes the total errors not to be normally distributed. However, without normality, according to Wooldridge, 2015, relying on asymptotic approximations is still possible. The estimations of this paper should be interpreted with the above limitations in mind.

5. Results

This chapter presents the results of the relationship between parental unemployment and children's educational attainment: completed years of schooling and the probability of college attendance[1]. The first part presents associations between parental unemployment and family characteristics with children's educational attainment in the sample; the second part shows the results from family fixed effects estimations; the third consists of heterogeneity analyses; and the fourth tests the robustness of the results.

[1]Note that the number of observations differ between model specifications as, in some cases, only one parent reports their schooling. Also, regressions on *Schooling* have more observations compared to regressions on *College* as the sample requires only the former one not to be missing.

5.1. OLS Estimates

Table 5.1 presents the results on ordinary least squares regressions for the association between the number of years under parental unemployment and children's completed years of schooling, whether the association is more substantial in certain childhood stages, and whether the association differs between low and highly educated families. The estimates show that one more year under parental unemployment between ages zero and 16 is not associated with years of completed schooling at age 25 when family characteristics such as parental education and father ever experiencing unemployment are controlled for (Regression 2). Adding an interaction between years under parental unemployment and whether parents are highly educated (Regression 3) shows the association is negative (one more year of parental unemployment is associated with 0.08 fewer completed years of schooling) and statistically significant (at 5% level) for low-educated families. However, the association does not have statistically significant differences between highly and low-educated families. When the associations are evaluated per age group (Regressions 4, 5 and 6), the association between *Years Unemployed* and *Schooling* show otherwise similar results to the non-grouped estimates except that the negative association in the family education-interacted specification disappears.

Table 5.2 repeats the estimations using college attendance as a dependent variable and shows no statistically significant evidence that one more year under parental unemployment between ages zero and 16 would be associated with the probability of college attendance nor that the association differs between highly and low-educated families. Moreover, estimating the per childhood stage associations between *Years Unemployed* and *Schooling* does not change the results.

OLS estimations reveal that parental education is important in explaining children's educational attainment. In addition, whether a father ever experienced unemployment explains variation in completed years of schooling in more model specifications than years under parental unemployment, although this is not the case when college attendance is used as a dependent variable. The finding can be interpreted as follows: children from families who experience parental unemployment receive fewer years of schooling. Whether this association is attributed to the effects of experiencing parental unemployment or to unobserved family characteristics (e.g., genes, inheritability of family endowments, ethnicity and regional location) should be evaluated by using more sophisticated models.

5.2. Fixed Effects Estimates

Table 5.3 shows the estimated effects of parental unemployment on children's completed years of schooling using the (within-sibling) family fixed effects model. The marginal effect of one more year under parental unemployment on children's completed years of schooling is not statistically significant, regardless of whether the effect is evaluated at the whole age interval or in different stages of childhood. The results show similar results when with and without control variables. Moreover, no statistically significant differences exist between parental unemployment's effect in highly and low-educated families.

Table 5.4 shows the marginal effect of one more year of parental unemployment using college attendance as a dependent variable. The results show no evidence that one more year of parental

Table 5.1

OLS Regression Estimates of Number of Years Under Parental Unemployment on Completed Years of Schooling

	(1) Schooling	(2) Schooling	(3) Schooling	(4) Schooling	(5) Schooling	(6) Schooling
Father Ever Unemployed		-0.456**	-0.346*		-0.457**	-0.350*
		(0.143)	(0.143)		(0.144)	(0.143)
Parent Schooling		0.180***			0.182***	
		(0.033)			(0.033)	
Years Unemployed (0-16)	-0.182***	-0.067	-0.083*			
	(0.035)	(0.036)	(0.042)			
Years Unemployed (0-4)				-0.147	-0.133	-0.174
				(0.082)	(0.079)	(0.097)
Years Unemployed (5-9)				-0.156*	0.016	0.012
				(0.077)	(0.077)	(0.094)
Years Unemployed (10-16)				-0.244**	-0.095	-0.103
				(0.079)	(0.077)	(0.095)
Parent Schooling High			1.097***			1.094***
			(0.203)			(0.204)
× Years Unemployed (0-16)			0.029			
			(0.069)			
× Years Unemployed (0-4)						0.098
						(0.155)
× Years Unemployed (5-9)						-0.045
						(0.150)
× Years Unemployed (10-16)						0.045
						(0.155)
Constant	14.086***	8.766***	10.874***	14.075***	8.712***	10.855***
	(0.124)	(0.606)	(0.487)	(0.125)	(0.609)	(0.490)
Controls		✓	✓		✓	✓
R-Squared	0.065	0.254	0.284	0.066	0.256	0.285
Observations	871	782	782	871	782	782

Notes. Indented variables are interactions with the previous non-indented variable. Controls represent the full set of control variables presented in Table 3.1. OLS, ordinary least squares. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5.2

OLS Regression Estimates of Years Under Parental Unemployment on College Attendance

	(1) College	(2) College	(3) College	(4) College	(5) College	(6) College
Father Ever Unemployed		-0.036	-0.013		-0.035	-0.012
		(0.035)	(0.034)		(0.035)	(0.035)
Parent Schooling		0.026^{***}			0.027^{***}	
		(0.008)			(0.008)	
Years Unemployed (0-16)	-0.028^{***}	-0.015	-0.017			
	(0.008)	(0.009)	(0.010)			
Years Unemployed (0-4)				-0.020	-0.023	-0.030
				(0.019)	(0.019)	(0.023)
Years Unemployed (5-9)				-0.014	0.007	0.005
				(0.017)	(0.019)	(0.023)
Years Unemployed (10-16)				-0.051^{**}	-0.031	-0.030
				(0.018)	(0.019)	(0.023)
Parent Schooling High			0.207^{***}			0.209^{***}
			(0.049)			(0.049)
× Years Unemployed (0-16)			0.009			
			(0.017)			
× Years Unemployed (0-4)						0.021
						(0.038)
× Years Unemployed (5-9)						0.003
						(0.036)
× Years Unemployed (10-16)						0.003
						(0.037)
Constant	0.785^{***}	-0.028	0.281^{*}	0.781^{***}	-0.046	0.271^{*}
	(0.028)	(0.147)	(0.118)	(0.028)	(0.148)	(0.118)
Controls		✓	✓		✓	✓
R-Squared	0.032	0.133	0.168	0.034	0.136	0.170
Observations	835	746	746	835	746	746

Notes. Indented variables are interactions with the previous non-indented variable. Controls represent the full set of control variables presented in Table 3.1. OLS, ordinary least squares. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table 5.3

FE Regression Estimates of Timing and Number of Years Under Parental Unemployment on Completed Years of Schooling

	(1) Schooling	(2) Schooling	(3) Schooling	(4) Schooling	(5) Schooling	(6) Schooling
Years Unemployed (0-16)	0.114	0.091	0.129			
	(0.085)	(0.096)	(0.123)			
Years Unemployed (0-4)				0.106	0.073	0.067
				(0.116)	(0.124)	(0.153)
Years Unemployed (5-9)				0.173	0.161	0.256
				(0.124)	(0.131)	(0.171)
Years Unemployed (10-16)				0.071	0.059	0.083
				(0.119)	(0.122)	(0.154)
Parent Schooling High						
× Years Unemployed (0-16)			-0.050			
			(0.187)			
× Years Unemployed (0-4)						0.046
						(0.238)
× Years Unemployed (5-9)						-0.171
						(0.265)
× Years Unemployed (10-16)						-0.061
						(0.267)
Constant	13.005***	13.354***	13.413***	13.005***	13.330***	13.417***
	(0.255)	(0.625)	(0.693)	(0.257)	(0.630)	(0.702)
Controls		✓	✓		✓	✓
R-Squared	0.018	0.054	0.067	0.019	0.056	0.070
Observations	871	871	784	871	871	784

Notes. Estimates from within-family fixed effects with family-clustered standard errors. Indented variables are interactions with the previous non-indented variable. Controls represent the full set of control variables presented in Table 3.1 excluding sibling invariant controls. Fe, fixed effects. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

unemployment between age zero and 16 reduces the probability of college attendance. However, evaluating the effects at different stages of childhood shows that the negative effect of highly educated families' parental unemployment between ages 10 and 16 reduces the probability of college attendance by 12% (statistically significant at a 5% level). The results hint that children from highly educated families, who are more likely to attend college, are vulnerable to parental unemployment at later childhood stages.

5.3. Heterogeneity Analyses

I expand the analyses by testing whether paternal and maternal unemployment have heterogeneous effects on children's educational attainment and whether parental unemployment has heterogeneous effects on boys and girls. The model is otherwise identical to the one in Section 5.2 with a difference in using father and mother-specific explanatory and control variables in

Table 5.4

FE Regression Estimates of Timing and Number of Years Under Parental Unemployment on College Attendance

	(1) College	(2) College	(3) College	(4) College	(5) College	(6) College
Years Unemployed (0-16)	0.025	0.006	0.040			
	(0.022)	(0.024)	(0.034)			
Years Unemployed (0-4)				0.034	0.012	0.055
				(0.032)	(0.034)	(0.052)
Years Unemployed (5-9)				0.035	0.019	0.050
				(0.031)	(0.033)	(0.049)
Years Unemployed (10-16)				0.006	-0.010	0.023
				(0.027)	(0.028)	(0.040)
Parent Schooling High						
× Years Unemployed (0-16)			-0.073			
			(0.044)			
× Years Unemployed (0-4)						-0.057
						(0.059)
× Years Unemployed (5-9)						-0.080
						(0.062)
× Years Unemployed (10-16)						-0.121*
						(0.059)
Constant	0.628***	0.850***	0.858***	0.622***	0.836***	0.850***
	(0.069)	(0.171)	(0.189)	(0.070)	(0.175)	(0.193)
Controls		✓	✓		✓	✓
R-Squared	0.017	0.054	0.069	0.019	0.056	0.075
Observations	835	835	748	835	835	748

Notes. Estimates from within-family fixed effects with family-clustered standard errors. Indented variables are interactions with the previous non-indented variable. Controls represent the full set of control variables presented in Table 3.1 excluding sibling invariant controls. Fe, fixed effects. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

columns specified with *Father* and *Mother*, respectively [2].

5.3.1. Paternal and Maternal Unemployment

The heterogeneous effects of fathers' and mothers' unemployment are presented in Table 5.5 where the first four columns show the father-specific estimates and the latter four the mother-specific ones. Years under paternal unemployment do not significantly affect children's completed years of schooling when the estimates are evaluated for all families (Regressions 1 and 3). However, including an interaction between years under paternal unemployment and whether a father is highly educated shows that one more year under paternal unemployment between ages zero and 16 reduces completed years of schooling of children of highly educated fathers by 0.70 years (statistically significant at 1% level). Furthermore, the education-interacted regression evaluated at different stages of childhood shows that the effect of unemployment of highly educated fathers is driven by unemployment during children ages zero to four; The marginal

[2] See Table 3.1 for details of which variables are transformed into father or mother specific ones.

Table 5.5

FE Regression Estimates of the Heterogeneous Effects of Paternal and Maternal Timing and Number of Years of Unemployment on Completed Years of Schooling

	Father				Mother			
	(1) Schooling	(2) Schooling	(3) Schooling	(4) Schooling	(5) Schooling	(6) Schooling	(7) Schooling	(8) Schooling
Years Unemployed (0-16)	0.033	0.233			0.077	0.142		
	(0.157)	(0.164)			(0.112)	(0.148)		
Years Unemployed (0-4)			-0.161	0.061			0.210	0.199
			(0.189)	(0.210)			(0.151)	(0.166)
Years Unemployed (5-9)			0.155	0.348			0.117	0.259
			(0.207)	(0.211)			(0.154)	(0.219)
Years Unemployed (10-16)			0.178	0.323			-0.058	0.053
			(0.178)	(0.190)			(0.156)	(0.201)
× Years Unemployed (0-16)		-0.701**				-0.121		
		(0.256)				(0.184)		
× Years Unemployed (0-4)				-0.855*				0.051
				(0.366)				(0.272)
× Years Unemployed (5-9)				-0.728				-0.301
				(0.376)				(0.292)
× Years Unemployed (10-16)				-0.372				-0.223
				(0.490)				(0.273)
Constant	13.786***	13.643***	13.608***	13.515***	13.255***	13.221***	13.056***	13.017***
	(0.717)	(0.705)	(0.714)	(0.701)	(0.766)	(0.758)	(0.752)	(0.748)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
R-Squared	0.078	0.103	0.093	0.119	0.080	0.081	0.086	0.089
Observations	474	474	474	474	647	647	647	647

Notes. Estimates from within-family fixed effects with family-clustered standard errors. Groups *Father* and *Mother* respectively include father and mother-specific variables of interest and control variables presented in Table 3.1. For father and mother-specific estimates, only families with at least one child who experienced paternal and maternal unemployment between ages zero and 16, respectively, are included. Indented variables are interactions with the previous non-indented variable. Controls represent the full set of control variables presented in Table 3.1 excluding sibling invariant controls. Fe, fixed effects. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

effect of one more year of unemployment reduces *Schooling* by 0.86 years (significant at 5% level). The mother-specific estimates show no statistically significant evidence that one more year of maternal unemployment would affect children's completed years of schooling. This finding holds for all age groups regardless of whether or not interactions with the mother's education are included.

The results differ when college attendance is used as a dependent variable (see A.4 in the Appendix). Neither paternal nor maternal unemployment affects the probability of college attendance in any of the model specifications. The estimates turning insignificant when the father's and mother's unemployment is evaluated separately may result from a lack of within-family variance in college attendance caused by the exclusion of families with no maternal and paternal unemployment from the father and mother-specific estimations, respectively.

5.3.2. Differential Effects Based on Sibling Gender

I include interactions between years under parental unemployment and children's gender in the family fixed effect model to identify parental unemployment's differential effects on boys and girls (Tables A.5 and A.6 in the Appendix for *Schooling* and *College*, respectively). I analyse the effects of parental, paternal and maternal unemployment separately. Using heterogeneous effects on boys and girls inevitably reduces the statistical power of the estimates, and the results should be interpreted with that caveat in mind[3]. The estimates reveal that neither parental, paternal, nor maternal unemployment differs in their effects on boys and girls regardless of whether the effect is estimated on completed years of schooling or college attendance.

5.4. Robustness

The results show that unemployment of highly educated fathers negatively affects children's completed years of schooling and that unemployment of highly educated parents negatively affects the probability of college attendance. In this section, I firstly analyse whether cross-parental influence drives father and mother-specific estimates; secondly, whether the effects of paternal unemployment are dependent on fathers' own education or family education; thirdly, the sensitivity of the estimates to changes in age intervals; fourthly, the findings' robustness to addressing reverse causality; and lastly the robustness of the findings to changes in the unemployment variable.

5.4.1. The Combined Influence of Paternal and Maternal Unemployment

Father and mother-specific variables are (somewhat unexpectedly) not strongly correlated with each other[4]. I test the robustness of paternal unemployment's effects on children by controlling for mothers' influence and the robustness of maternal unemployment's effects on children by controlling for fathers' influence by including both father and mother-specific variables in the regressions (See Tables A.7 and A.8 in the Appendix for *Schooling* and *College*, respectively). For example, if paternal and maternal unemployment both negatively affect children's educational attainment and the father experienced several years of unemployment at a given age interval of his child, then failing to control for the mother's years of unemployment would exaggerate the effect of paternal unemployment if the mother also experienced several years of unemployment during the same age interval.

The results regarding completed years of schooling show that the negative effect of unemployment of highly educated fathers in children ages zero to 16 and in the age interval from zero to four both survive controlling maternal influence. In addition, the effects of maternal unemployment stay statistically insignificant. On the other hand, estimating the effects on college attendance changes maternal unemployment's effects in the entire age interval (in Regression 1 without interaction with maternal education) to positive and statistically significant (at a %5 level). Using childhood stage-specific estimations reveals that the finding is driven by the age group from five to nine.

5.4.2. Paternal vs. Family Education in Explaining the Effects of Paternal Unemployment

Earlier estimations (in Table 5.5) showed paternal unemployment negatively and significantly affects children's completed years of schooling if the father is highly educated. I investigate

[3] 46.2%, 43.9% and 44.5% of siblings in parent, father, and mother-specific estimates have variation in both experienced unemployment and gender in their family.

[4] Correlation matrix including all father and mother-specific variables shows correlations never stronger than 0.47

whether the effects of years under paternal unemployment depend on the father's educational level or whether the family is highly educated. The results (See Table A.9 in the Appendix) show that fathers' education rather than family education matters for paternal unemployment's effects. The estimates turn insignificant in all age intervals when paternal unemployment's interaction with the father's education is replaced with an interaction with the average family or the mother's education.

5.4.3. Using Alternative Age Intervals

I analyse how sensitive parental unemployment's effects are to changes in the age intervals at which unemployment's effects are evaluated. I expanded the entire age interval to range from zero to 22 years and changed age groups to zero to seven, eight to 16 and 17 to 22. A higher upper limit is chosen to increase the number of observations per group and to include the possible influence of parental unemployment experiences in late teens and early adulthood.

The results (See Table A.10 and A.11 in the Appendix for *Schooling* and *College*, respectively) show that altering age groups does not affect how parental unemployment (either father or mother unemployed) affects completed years of schooling as all the estimates stay insignificant. The father-specific estimates show that the effect of experiencing one more year of unemployment of highly educated fathers between ages zero and 22 is statistically insignificant. However, paternal unemployment's effect in the age interval from zero to seven is negative and statistically significant (at 1% level). In the age interval from 17 to 22, it is positive and statistically significant (at a 5% level), the latter of which likely drives the coefficient of the entire age interval to be insignificant. Furthermore, mother-specific estimates for the entire age interval and age interval from zero to seven turn positive and statistically significant in regressions that include interactions with education, and there is no statistically significant evidence that maternal unemployment's effects would differ between highly and low-educated mothers. Moreover, none of the coefficients for unemployment effects on the probability of college attendance are significant. The results show the effects of highly educated parents' unemployment during children ages 10 to 16 are not robust to age interval adjustments as the coefficient for age group eight to 16 is insignificant.

Overall, using adjusted age intervals reveals that including information about late teens and early adulthood helps explain children's completed years of schooling and that the effects of experiences of highly educated fathers' unemployment, driven by early childhood experiences, are robust to interval adjustments[5]. Furthermore, the age interval adjustments reveal parental unemployment's effects on the probability of college attendance not to be robust[6].

5.4.4. Reverse Causality

I include additional information about children's birth weight, whether children are reported to be in poor health and whether a family has a newborn child to address possible issues of reverse causality. These children's characteristics may reveal information about whether a parent chose

[5] I additionally confirm that the paternal unemployment-specific results (in Regressions 1, 2, 3 and 4) found in 5.5 are not affected if the age interval from 17 to 22 is included.

[6] I additionally confirm that the parental unemployment-specific results (in Regression 6) found in 5.4 become insignificant if the age interval from 17 to 22 is included.

to become or got unemployed due to reasons related to bad health or a disability of a child or to take care of a newborn child.

I re-run the fixed effects estimates by using the additional information as follows. I (*i*) exclude the years of parental unemployment when a child was reported to be in bad health and add a variable for the count of reported bad health in a given age interval, (*ii*) control for children's birth weight[7][8], and (*iii*) add a restriction in *Years Unemployed* by excluding the years when a family has a newborn (a child aged zero to one) in the family. It should be kept in mind that in the family-fixed effect model, these additional variables can only provide more information if the variables vary between siblings. For instance, if all the children in a family are born with a low birth weight due to a disability, little additional information is revealed.

Tables A.12 and A.13 in the Appendix show the reverse causality-adjusted fixed effects results for *Schooling* and *College*, respectively. Regarding completed years of schooling, parental unemployment's (either father or mother unemployed) effects stay insignificant. Moreover, maternal unemployment's effects show no changes and stay insignificant, whereas paternal unemployment's effects show some changes in estimated coefficients. The effect of one more year of paternal unemployment of low-educated fathers becomes positive and significant for the entire age interval and age groups from five to 16 (all at a 5% level), while the negative differential effect of highly educated fathers' unemployment stays statistically significant in the age interval from zero to four and becomes significant (at a 5% level) in the age interval from five to nine. It should be noted that the negative differential effect of unemployment of highly educated fathers dominates the positive effect of unemployment of low-educated fathers (except for in the age interval from 10 to 16, where the coefficient for highly educated fathers' unemployment is insignificant); One more year of paternal unemployment between ages zero and 16 increases the completed years of schooling of children of low-educated fathers by 0.47 years and reduces the completed years of schooling of children of highly-educated fathers by 0.51 years (0.467 - 0.981 years). The results show the negative effects of paternal unemployment of highly educated fathers to be robust to reverse causality-related adjustments. Furthermore, the reverse causality-related adjustments do not change (parental, paternal and maternal) unemployment's insignificant effects on the probability of college attendance.

5.4.5. Layoffs Induced Measurement Error

This paper considers a person unemployed if they report being *only temporarily laid-off* or *unemployed, looking for work* as their employment status. I address the possible error in estimating the effects of unemployment that may be caused by including temporary layoffs in the variable by evaluating layoffs and unemployment's effects separately. Tables A.14 and A.15 in

[7]The data for children's birth weight is inconsistent and is missing 53.7% of actual birth weights. For many children, only whether their birth weight is low (under 88 ounces) is reported. I use this additional data to construct the birth weight variable as follows. The birth weight equals either the actual birth weight if it is reported; the average birth weight of siblings if the average birth weight is below 88 ounces and the child's birth weight is reported to be low; the average birth weight of siblings if the average birth weight is or above 88 ounces and the child's birth weight is reported not to be low; to be conservative, 88 ounces if the average birth weight and whether a child's birth weight is low are conflicting; and the average birth weight in the sample if the birthweight is missing for all siblings (to avoid reduction of the statistical power of the estimates although biasing birth weight's effects towards zero). In the adjusted birth weight variable, 37.0% of the values are missing; thus, the variable is only included in this robustness check phase.

[8]Lower birth weight children are found to have lower educational attainment Black et al., 2007

the Appendix present unemployment's and layoff's effects on *Schooling*, while Tables A.16 and A.17 present the same effects on *College*. Unemployment and layoff variables are both included in all regressions[9] although presented in separate tables for spatial reasons.

The results from unemployment's effects on completed years of schooling show that none of the previously significant effects survives the exclusion of layoffs. The negative effect of highly educated fathers' unemployment becomes insignificant, while low-educated fathers' unemployment during children ages five to nine becomes positive and statistically significant (at a 5% level). The insignificance of the estimates is not likely to be caused by reductions in the statistical power of the estimates as the number of children who have within-family variation in experiences of paternal unemployment in the entire age interval drops from 254 to 230 while the same number for children of highly-educated fathers drops from 78 to 72. On the other hand, The estimates on the effects of layoffs show the effect of highly educated fathers' unemployment for the entire age interval to be negative and statistically significant (at a 5% level). Furthermore, the effect of layoffs of low-educated mothers is positive and significant during the entire age interval and age groups zero to four and five to nine. Additionally, the effect of layoff of highly-educated mothers is negative and significant for the age group 10 to 16.

Unemployment's effects on the probability of college attendance show similar insignificant results as for completed years of schooling. On the other hand, the estimates on layoff's effects reveal that layoffs of low-educated mothers have a positive effect on children's probability of college attendance in the entire age interval and for age groups five to nine and 10 to 16, while the differential effect of layoffs of highly educated mothers is negative for children aged 10 to 16, slightly dominating the positive effect for the same age group.

Overall, estimating unemployment's and layoffs' effects separately reveals layoffs and unemployment likely together drive the significant results found for unemployment of highly educated fathers regarding completed years of schooling. In addition, Maternal layoffs' statistically significant effects on both completed years of schooling and the probability of college attendance show that maternal layoffs influence children's educational attainment more than maternal unemployment.

6. Conclusions and Discussion

This paper provides empirical evidence on the relationship between parental unemployment and children's skills formation. I use a family fixed effects model that utilises the variation in siblings' age difference during parental unemployment to explain parental unemployment's effects on children's completed years of schooling and the probability of college attendance. The data is retrieved from the Panel Study of Income Dynamics, a longitudinal survey from the United States. The results show evidence that parental education affects children's educational attainment only in a few specific cases of unemployment and that children are the most vulnerable to unemployment of highly educated fathers.

To answer how parental unemployment affects children's skills formation, I hypothesise that: (*i*) the time under parental unemployment reduces children's educational attainment, (*ii*)

[9] There are no strong correlations between the new unemployment variable and the layoff variable.

parental unemployment's effects are stronger in low-educated families, and (*iii*) for younger ages. First, I find that an additional year under parental unemployment only reduces children's educational attainment on specific occasions. The finding is weaker than expected based on Lesner, 2018, who found that an additional year of low disposable income reduces children's years of schooling regardless of age or parent's education level. Second, I do not find evidence that parental unemployment would be stronger in lower-educated families; in contrast, the most substantial evidence of unemployment's effects is found for highly educated fathers. This finding does not support the findings of Dahl and Lochner, 2012, which finds disadvantaged families more affected by income changes. Third, I find support for younger children to be more vulnerable to parental unemployment regarding the effects on completed years of schooling; however, this is only for unemployment of highly educated fathers, whose unemployment has significant negative effects during early childhood and positive effects during the few years preceding or during college age. The finding is in line with the theoretical prediction of a higher rate of return on human capital for younger children by Heckman, 2000 but contrasts the empirical findings of Lesner, 2018, according to whom an additional year of low disposable income reduces children's years of schooling more if a child is older. Furthermore, I find no (robust) evidence the probability of college attendance would be affected. At the same time, robustness tests reveal that the findings regarding children's completed years of schooling are robust to adjustments in age intervals and to reverse causality caused by children's health and the presence of newborns in the family. However, parental layoffs may play a role in driving the effects of both completed years of schooling and the probability of college attendance.

The intergenerational effects of parental unemployment may not be sufficiently considered in planning economic policies related to unemployment benefits and employment protection. The findings of this paper tell that although parental unemployment does not harm all children's skills formation, a reduction in skills of the next generation could be alleviated by protecting children of highly educated fathers[1] from paternal unemployment. However, the effectiveness of using measures that would alleviate unemployment's effects on intergenerational skills formation depends on the extent to which reductions in children's educational attainment are attributed to reductions in family income caused by unemployment. Based on human capital theories by Becker and Tomes, 1979, 1986; Cunha and Heckman, 2007; Heckman, 2000, two possible mechanisms through which unemployment of highly educated fathers may negatively affect children's skills formation can be identified. First, highly educated fathers' contribution to family income may be significant, and therefore, those fathers' unemployment may lead to reduced investments in children. Second, unemployment of highly educated fathers may have significant effects on family environments as highly educated fathers may be affected the most by losses of social status and, therefore, negatively affect children's non-cognitive skills and motivation. In theory, if unemployment's negative effects are driven mainly by its negative effects on family environments, then the next generation would benefit from stricter employment protection. However, if parental unemployment has negative intergenerational effects due to income reductions, then both stricter employment protection and higher unemployment benefits would benefit the next generation's skills. Unfortunately, the lack of availability of income data

[1] It should be noted that this paper does not recommend employment measures that preferentially treat any genders or income levels, but only notes the specific group in which the strongest evidence is found

does not allow me to analyse further the extent to which income losses and family environments drive the empirical findings. Comparing my results to the ones found by Lesner, 2018, who finds stronger negative effects by using years under family poverty in explaining children's completed years of schooling, may not reveal additional information about the mechanism either, as family poverty is likely to be more strongly correlated with both family income and family environments than parental unemployment. Thus, I will leave the question about the driving mechanism of my findings for further research.

The reliability of drawing causal relations between parental unemployment and educational attainment based on the analysis of this paper depends on whether parental unemployment is exogenous, measured accurately, and whether the sample has sufficient statistical power. First, limitations in data (and its availability) on time or sibling-variant unobserved family characteristics, such as income changes and residential moves, may be a cause of bias in the estimations. Second, the lack of an alternative measure or cross-validation of the unemployment variable may lead to measurement error. Third, the estimations, especially the ones with interactions and restrictions, may have too low a number of observations with variation in between-sibling experiences of parental unemployment to avoid false-negative or lack of generalizability of results. Nevertheless, this paper helps to contribute to the understanding of unemployment's intergenerational effects in the US context by identifying (*i*) which childhood periods are vulnerable to parental unemployment, (*ii*) the role of parents' education in the effects, (*iii*) the differential effects of paternal and maternal unemployment, and finally, (*iv*) providing a framework for future research into possible mechanisms through which parental unemployment affects children's skills formation.

Appendix A. Tables and Figures

Table A.1

Number and Share of Children in the Sample with Within-Family Variation in Experienced Parental Unemployment, Stratified by Age Group

	Parental Unemployment		Paternal Unemployment		Maternal Unemployment	
	Number	Share	Number	Share	Number	Share
Years Unemployed						
Ages 0-16	501	0.58	254	0.29	359	0.41
Ages 0-4	455	0.52	241	0.28	296	0.34
Ages 5-9	452	0.52	263	0.30	292	0.34
Ages 10-16	399	0.46	207	0.24	254	0.29
Total	871	1.00	871	1.00	871	1.00

Notes. The table describes the number and share of children in the sample that have within-family variation in their experienced parental unemployment, paternal unemployment and maternal unemployment. The shares show the share of children related to the number of children in the total sample.

Table A.2

Number and Share of Children in the Sample with Within-Family Variation in Experienced Parental Unemployment and Highly-Educated Parents, Father and Mother, Stratified by Age Group

	Parental Unemployment, Highly-Educated Parents		Paternal Unemployment, Highly-Educated Father		Maternal Unemployment, Highly-Educated Mother	
	Number	Share	Number	Share	Number	Share
Years Unemployed						
Ages 0-16	214	0.25	78	0.09	183	0.21
Ages 0-4	214	0.25	61	0.07	159	0.18
Ages 5-9	185	0.21	73	0.08	130	0.15
Ages 10-16	130	0.15	46	0.05	90	0.10
Total	871	1.00	871	1.00	871	1.00

Notes. The table describes the number and share of children of highly educated parents in the sample that have within-family variation in their experienced parental unemployment, paternal unemployment and maternal unemployment. The shares show the share of children related to the number of children in the total sample.

Table A.3

Mandatory Schooling in US States in 2017

State	Age of Required School Attendance	Number of Years
Alabama	6 to 17	11
Alaska	7 to 16	9
Arizona	6 to 16	10
Arkansas	5 to 18	13
California	6 to 18	12
Colorado	6 to 17	11
Connecticut	5 to 18	13
Delaware	5 to 16	11
District of Columbia	5 to 18	13
Florida	6 to 16	10
Georgia	6 to 16	10
Hawaii	5 to 18	13
Idaho	7 to 16	9
Illinois	6 to 17	11
Indiana	7 to 18	11
Iowa	6 to 16	10
Kansas	7 to 18	11
Kentucky	6 to 18	12
Louisiana	7 to 18	11
Maine	7 to 17	10
Maryland	5 to 18	13
Massachusetts	6 to 16	10
Michigan	6 to 18	12
Minnesota	7 to 17	10
Mississippi	6 to 17	11
Missouri	7 to 17	10
Montana	7 to 16	9
Nebraska	6 to 18	12
Nevada	7 to 18	11
New Hampshire	6 to 18	12
New Jersey	6 to 16	10
New Mexico	5 to 18	13
New York	6 to 16	10
North Carolina	7 to 16	9
North Dakota	7 to 16	9
Ohio	6 to 18	12

Notes. Number of years constructed from the age of required school attendance. *Source.* National Center for Education Statistics NCES, 2020.

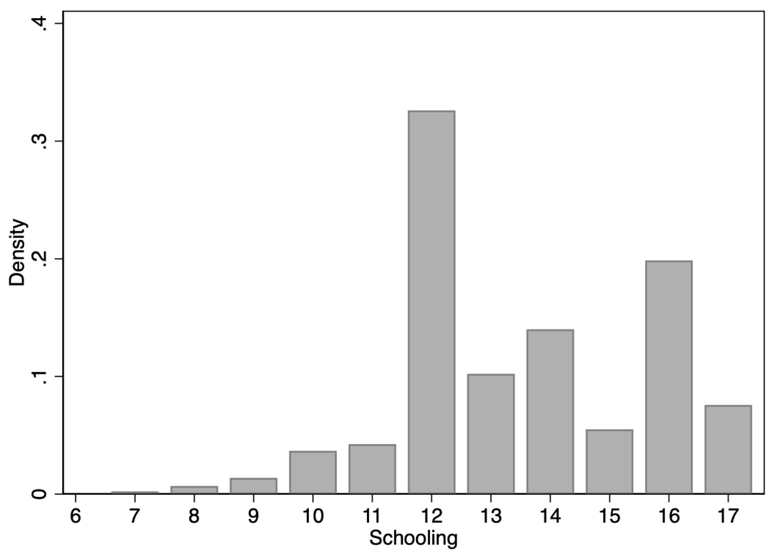

Figure A.1. The Distribution of Children's Completed Years of Schooling in the Sample . Completed years of schooling on the x-axis and the proportion of observations with the given value of completed years of schooling on the y-axis. *Data Source.* Panel Study of Income Dynamics.

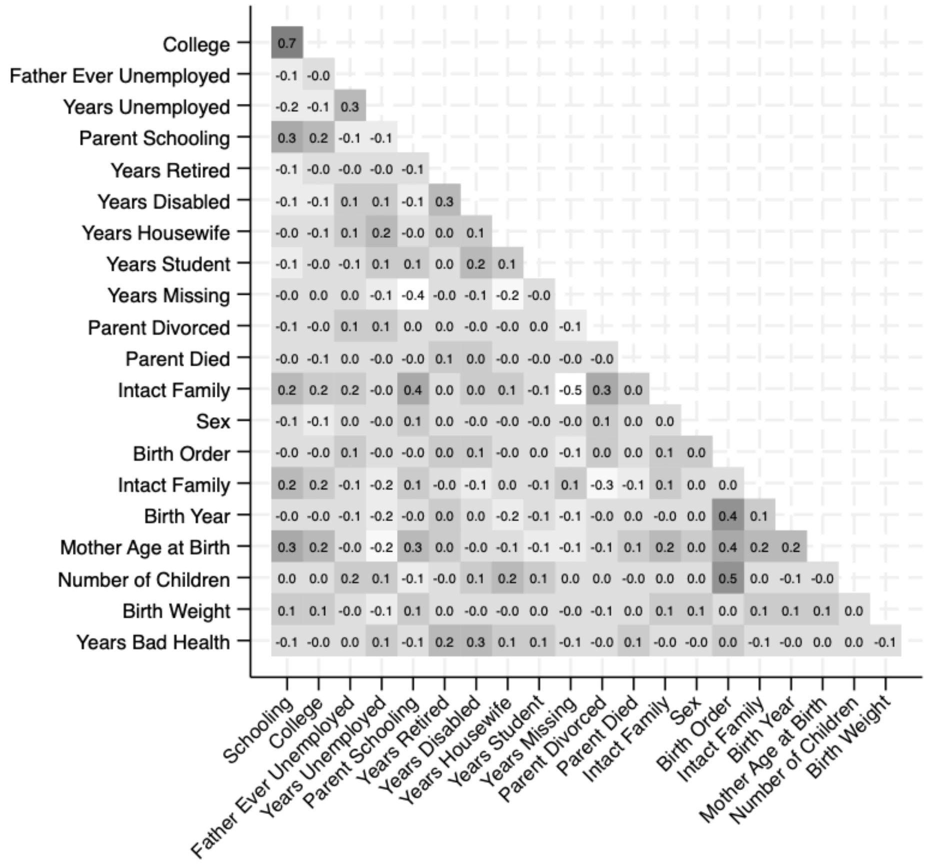

Figure A.2. Correlation Matrix for Variables. The variable correlations range from negative correlation (white) to no correlation (light grey) to positive correlation (dark grey). The variable explanations are provided in Table 3.1. *Data Source.* Panel Study of Income Dynamics.

Table A.4

FE Regression Estimates of the Heterogeneous Effects of Paternal and Maternal Timing and Number of Years of Unemployment on College Attendance

	Father				Mother			
	(1) College	(2) College	(3) College	(4) College	(5) College	(6) College	(7) College	(8) College
Years Unemployed (0-16)	-0.027 (0.035)	0.000 (0.041)			0.007 (0.031)	0.045 (0.043)		
Years Unemployed (0-4)			-0.034 (0.050)	-0.003 (0.059)			0.010 (0.044)	0.039 (0.058)
Years Unemployed (5-9)			-0.029 (0.044)	-0.009 (0.052)			0.047 (0.052)	0.105 (0.071)
Years Unemployed (10-16)			-0.015 (0.044)	0.018 (0.048)			-0.017 (0.037)	0.017 (0.056)
× Years Unemployed (0-16)		-0.088 (0.066)				-0.070 (0.050)		
× Years Unemployed (0-4)				-0.087 (0.095)				-0.051 (0.072)
× Years Unemployed (5-9)				-0.056 (0.077)				-0.120 (0.083)
× Years Unemployed (10-16)				-0.135 (0.125)				-0.062 (0.069)
Constant	0.906*** (0.185)	0.889*** (0.185)	0.902*** (0.186)	0.880*** (0.188)	0.956*** (0.220)	0.940*** (0.216)	0.920*** (0.235)	0.909*** (0.233)
Controls	✓	✓	✓	✓	✓	✓	✓	✓
R-Squared	0.063	0.069	0.064	0.070	0.074	0.078	0.078	0.085
Observations	449	449	449	449	620	620	620	620

Notes. Estimates from within-family fixed effects with family-clustered standard errors. Groups *Father* and *Mother* respectively include father and mother-specific variables of interest and control variables presented in Table 3.1. For father and mother-specific estimates, only families with at least one child who experienced paternal and maternal unemployment between ages zero and 16, respectively, are included. Indented variables are interactions with the previous non-indented variable. Controls represent the full set of control variables presented in Table 3.1 excluding sibling invariant controls. Fe, fixed effects. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.5

FE Regression Estimates of the Heterogeneous Effects of Timing and Number of Years of Parental Unemployment on Completed Years of Schooling of Boys and Girls

	Parents		Father		Mother	
	(1) Schooling	(2) Schooling	(3) Schooling	(4) Schooling	(5) Schooling	(6) Schooling
Years Unemployed (0-16)	0.078		0.053		0.052	
	(0.103)		(0.160)		(0.130)	
Years Unemployed (0-4)		-0.000		-0.291		0.150
		(0.145)		(0.197)		(0.174)
Years Unemployed (5-9)		0.172		0.279		0.108
		(0.142)		(0.206)		(0.208)
Years Unemployed (10-16)		0.090		0.299		-0.087
		(0.132)		(0.207)		(0.182)
Sex Male						
× Years Unemployed (0-16)	0.022		-0.042		0.042	
	(0.056)		(0.056)		(0.111)	
× Years Unemployed (0-4)		0.155		0.280		0.128
		(0.141)		(0.175)		(0.224)
× Years Unemployed (5-9)		-0.014		-0.190		-0.007
		(0.147)		(0.183)		(0.218)
× Years Unemployed (10-16)		-0.065		-0.185		0.055
		(0.128)		(0.150)		(0.192)
Constant	13.387***	13.350***	13.745***	13.483***	13.303***	13.106***
	(0.633)	(0.636)	(0.720)	(0.699)	(0.779)	(0.768)
Controls	✓	✓	✓	✓	✓	✓
R-Squared	0.055	0.058	0.079	0.106	0.081	0.086
Observations	871	871	474	474	647	647

Notes. Estimates from within-family fixed effects with family-clustered standard errors. Groups *Father* and *Mother* respectively include father and mother-specific variables of interest and control variables presented in Table 3.1. For father and mother-specific estimates, only families with at least one child who experienced paternal and maternal unemployment between ages zero and 16, respectively, are included. Indented variables are interactions with the previous non-indented variable. Controls represent the full set of control variables presented in Table 3.1 excluding sibling invariant controls. Fe, fixed effects. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.6

FE Regression Estimates of the Heterogeneous Effects of Timing and Number of Years of Parental Unemployment on College Attendance of Boys and Girls

	Parents		Father		Mother	
	(1) College	(2) College	(3) College	(4) College	(5) College	(6) College
Years Unemployed (0-16)	0.005		-0.030		0.004	
	(0.026)		(0.035)		(0.039)	
Years Unemployed (0-4)		-0.005		-0.067		-0.002
		(0.038)		(0.056)		(0.049)
Years Unemployed (5-9)		0.026		-0.012		0.046
		(0.037)		(0.045)		(0.062)
Years Unemployed (10-16)		-0.001		-0.010		-0.012
		(0.034)		(0.052)		(0.050)
Sex Male						
× Years Unemployed (0-16)	0.001		0.008		0.004	
	(0.015)		(0.015)		(0.030)	
× Years Unemployed (0-4)		0.035		0.060		0.024
		(0.040)		(0.049)		(0.064)
× Years Unemployed (5-9)		-0.012		-0.029		-0.001
		(0.039)		(0.051)		(0.062)
× Years Unemployed (10-16)		-0.016		-0.001		-0.013
		(0.033)		(0.042)		(0.050)
Constant	0.852^{***}	0.833^{***}	0.914^{***}	0.902^{***}	0.961^{***}	0.920^{***}
	(0.171)	(0.176)	(0.185)	(0.186)	(0.223)	(0.240)
Controls	✓	✓	✓	✓	✓	✓
R-Squared	0.054	0.058	0.064	0.068	0.074	0.079
Observations	835	835	449	449	620	620

Notes. Estimates from within-family fixed effects with family-clustered standard errors. Groups *Father* and *Mother* respectively include father and mother-specific variables of interest and control variables presented in Table 3.1. For father and mother-specific estimates, only families with at least one child who experienced paternal and maternal unemployment between ages zero and 16, respectively, are included. Indented variables are interactions with the previous non-indented variable. Controls represent the full set of control variables presented in Table 3.1 excluding sibling invariant controls. Fe, fixed effects. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.7

FE Regression Estimates of the Heterogeneous Effects of Paternal and Maternal Timing and Number of Years of Unemployment on Completed Years of Schooling by Controlling the Other Parents's Effects

	(1) Schooling	(2) Schooling	(3) Schooling	(4) Schooling
Father				
Years Unemployed	0.016	0.224		
	(0.158)	(0.169)		
Years Unemployed (0-4)			-0.181	0.059
			(0.187)	(0.215)
Years Unemployed (5-9)			0.161	0.366
			(0.205)	(0.215)
Years Unemployed (10-16)			0.138	0.288
			(0.183)	(0.201)
Father Schooling High				
× Years Unemployed		-0.660*		
		(0.265)		
× Years Unemployed (0-4)				-0.847*
				(0.375)
× Years Unemployed (5-9)				-0.678
				(0.382)
× Years Unemployed (10-16)				-0.406
				(0.509)
Mother				
Years Unemployed (0-16)	0.070	0.029		
	(0.198)	(0.224)		
Years Unemployed (0-4)			0.157	0.122
			(0.221)	(0.244)
Years Unemployed (5-9)			0.214	0.337
			(0.307)	(0.347)
Years Unemployed (10-16)			-0.336	-0.366
			(0.277)	(0.329)
Mother Schooling High				
× Years Unemployed (0-16)		0.191		
		(0.422)		
× Years Unemployed (0-4)				0.204
				(0.535)
× Years Unemployed (5-9)				-0.187
				(0.646)
× Years Unemployed (10-16)				0.186
				(0.609)
Constant	13.148***	13.017***	13.069***	12.964***
	(0.929)	(0.953)	(0.903)	(0.949)
Controls	✓	✓	✓	✓
R-Squared	0.096	0.118	0.122	0.148
Observations	474	474	474	474

Notes. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Estimates from within-family fixed effects with family-clustered standard errors. Both father and mother-specific variables, presented in Table 3.1 are included together in the regressions. Controls represent the full set of control variables presented in Table 3.1 excluding sibling invariant controls. Fe, fixed effects. Indented variables are interactions with the previous non-indented variable.

Table A.8

FE Regression Estimates of the Heterogeneous Effects of Paternal and Maternal Timing and Number of Years of Unemployment on College Attendance by Controlling the Other Parents's Effects

	(1) College	(2) College	(3) College	(4) College
	Father			
Years Unemployed (0-16)	-0.013	0.027		
	(0.035)	(0.042)		
Years Unemployed (0-4)			-0.018	0.033
			(0.051)	(0.064)
Years Unemployed (5-9)			-0.011	0.030
			(0.045)	(0.058)
Years Unemployed (10-16)			-0.011	0.040
			(0.044)	(0.049)
Father Schooling High				
× Years Unemployed (0-16)		-0.122		
		(0.069)		
× Years Unemployed (0-4)				-0.129
				(0.104)
× Years Unemployed (5-9)				-0.097
				(0.084)
× Years Unemployed (10-16)				-0.179
				(0.123)
	Mother			
Years Unemployed (0-16)	0.124*	0.134		
	(0.057)	(0.072)		
Years Unemployed (0-4)			0.125	0.123
			(0.070)	(0.092)
Years Unemployed (5-9)			0.177*	0.209
			(0.088)	(0.106)
Years Unemployed (10-16)			0.072	0.120
			(0.090)	(0.112)
Mother Schooling High				
× Years Unemployed (0-16)		-0.022		
		(0.114)		
× Years Unemployed (0-4)				0.047
				(0.138)
× Years Unemployed (5-9)				-0.086
				(0.180)
× Years Unemployed (10-16)				-0.142
				(0.182)
Constant	0.614*	0.623*	0.605*	0.592*
	(0.252)	(0.259)	(0.250)	(0.262)
Controls	✓	✓	✓	✓
R-Squared	0.088	0.097	0.093	0.107
Observations	449	449	449	449

Notes. Estimates from within-family fixed effects with family-clustered standard errors. Both father and mother-specific variables, presented in Table 3.1 are included together in the regressions. Indented variables are interactions with the previous non-indented variable. Controls represent the full set of control variables presented in Table 3.1 excluding sibling invariant controls. Fe, fixed effects. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.9

FE Regression Estimates of Effects of Paternal Timing and Number of Years of Unemployment on Completed Years of Schooling Using Alternative Family Education Interactions

	Father, Highly Educated Family		Father, Highly Educated Mother	
	(1) Schooling	(2) Schooling	(3) Schooling	(4) Schooling
Years Unemployed (0-16)	0.092		0.168	
	(0.172)		(0.182)	
Years Unemployed (0-4)		-0.068		-0.106
		(0.203)		(0.205)
Years Unemployed (5-9)		0.211		0.397
		(0.227)		(0.224)
Years Unemployed (10-16)		0.183		0.171
		(0.207)		(0.221)
Family/Mother Schooling High				
× Years Unemployed (0-16)	-0.208		-0.307	
	(0.266)		(0.242)	
× Years Unemployed (0-4)		-0.338		-0.223
		(0.389)		(0.346)
× Years Unemployed (5-9)		-0.262		-0.609
		(0.390)		(0.349)
× Years Unemployed (10-16)		0.034		0.024
		(0.326)		(0.300)
Constant	13.907***	13.763***	13.763***	13.710***
	(0.733)	(0.734)	(0.715)	(0.724)
Controls	✓	✓	✓	✓
R-Squared	0.088	0.103	0.084	0.111
Observations	457	457	474	474

Notes. Estimates from within-family fixed effects with family-clustered standard errors. *Family/Mother Schooling High* represents variable *Parent Schooling High* in regresion group *Father, Highly Educated Family* and variable *Mother Schooling High* in regresion group *Father, Highly Educated Mother*. Groups *Father* and *Mother* respectively include father and mother-specific variables of interest and control variables presented in Table 3.1. For father and mother-specific estimates, only families with at least one child who experienced paternal and maternal unemployment between ages zero and 16, respectively, are included. Indented variables are interactions with the previous non-indented variable. Controls represent the full set of control variables presented in Table 3.1 excluding sibling invariant controls. Fe, fixed effects. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.10

FE Regression Estimates of the Heterogeneous Effects of Paternal and Maternal Timing and Number of Years of Unemployment on Completed Years of Schooling Using Alternative Age Intervals

	Parents				Father				Mother			
	(1) Schooling	(2) Schooling	(3) Schooling	(4) Schooling	(5) Schooling	(6) Schooling	(7) Schooling	(8) Schooling	(9) Schooling	(10) Schooling	(11) Schooling	(12) Schooling
Years Unemployed (0-22)	0.077	0.071			-0.121	-0.010			0.239	0.354*		
	(0.090)	(0.130)			(0.143)	(0.157)			(0.126)	(0.150)		
Years Unemployed (0-7)			0.120	0.182			-0.065	0.187			0.237	0.355*
			(0.110)	(0.154)			(0.165)	(0.180)			(0.124)	(0.151)
Years Unemployed (8-16)			0.061	0.053			-0.041	0.003			0.135	0.291
			(0.121)	(0.180)			(0.192)	(0.212)			(0.179)	(0.214)
Years Unemployed (17-22)			0.001	-0.104			-0.359	-0.518			0.395	0.433
			(0.153)	(0.191)			(0.257)	(0.310)			(0.204)	(0.236)
Parent Schooling High												
× Years Unemployed (0-22)		0.059				-0.433				-0.226		
		(0.181)				(0.273)				(0.191)		
× Years Unemployed (0-7)				-0.106				-0.992**				-0.199
				(0.212)				(0.312)				(0.223)
× Years Unemployed (8-16)				0.137				0.240				-0.287
				(0.241)				(0.373)				(0.258)
× Years Unemployed (17-22)				0.461				1.115*				0.015
				(0.387)				(0.484)				(0.453)
Constant	13.411***	13.415***	13.350***	13.232***	14.118***	14.070***	13.979***	13.807***	12.572***	12.537***	12.638***	12.525***
	(0.662)	(0.715)	(0.666)	(0.723)	(0.759)	(0.756)	(0.775)	(0.765)	(0.880)	(0.860)	(0.853)	(0.841)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R-Squared	0.046	0.057	0.047	0.063	0.031	0.040	0.039	0.096	0.073	0.076	0.078	0.081
Observations	871	784	871	784	474	474	474	474	647	647	647	647

Notes. Estimates from within-family fixed effects with family-clustered standard errors. Groups *Father* and *Mother* respectively include father and mother-specific variables of interest and control variables presented in Table 3.1. For father and mother-specific estimates, only families with at least one child who experienced paternal and maternal unemployment between ages zero and 16, respectively, are included. Indented variables are interactions with the previous non-indented variable. Controls represent the full set of control variables presented in Table 3.1 excluding sibling invariant controls. Fe, fixed effects. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.11

FE Regression Estimates of the Heterogeneous Effects of Paternal and Maternal Timing and Number of Years of Unemployment on College Attendance Using Alternative Age Intervals

	Parents				Father				Mother			
	(1) College	(2) College	(3) College	(4) College	(5) College	(6) College	(7) College	(8) College	(9) College	(10) College	(11) College	(12) College
Years Unemployed (0-22)	0.010	0.035			-0.025	-0.013			0.019	0.023		
	(0.025)	(0.033)			(0.039)	(0.044)			(0.032)	(0.046)		
Years Unemployed (0-7)			0.019	0.064			-0.027	0.002			0.029	0.065
			(0.029)	(0.042)			(0.044)	(0.052)			(0.037)	(0.050)
Years Unemployed (8-16)			-0.002	0.030			-0.040	-0.030			0.012	0.027
			(0.031)	(0.046)			(0.053)	(0.058)			(0.036)	(0.057)
Years Unemployed (17-22)			0.000	-0.020			-0.006	-0.039			-0.001	-0.058
			(0.037)	(0.047)			(0.055)	(0.059)			(0.060)	(0.072)
Parent Schooling High												
× Years Unemployed (0-22)		-0.053				-0.045				-0.007		
		(0.040)				(0.066)				(0.051)		
× Years Unemployed (0-7)				-0.091				-0.098				-0.054
				(0.050)				(0.078)				(0.061)
× Years Unemployed (8-16)				-0.063				0.003				-0.015
				(0.050)				(0.105)				(0.061)
× Years Unemployed (17-22)				0.091				0.182				0.219
				(0.074)				(0.144)				(0.113)
Constant	0.746***	0.749***	0.742***	0.713***	0.865***	0.863***	0.885***	0.863***	0.809***	0.808***	0.798***	0.744***
	(0.188)	(0.189)	(0.191)	(0.192)	(0.205)	(0.206)	(0.210)	(0.211)	(0.222)	(0.223)	(0.222)	(0.213)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R-Squared	0.045	0.047	0.046	0.057	0.051	0.052	0.052	0.063	0.064	0.064	0.065	0.079
Observations	835	835	835	835	449	449	449	449	620	620	620	620

Notes. Estimates from within-family fixed effects with family-clustered standard errors. Groups *Father* and *Mother* respectively include father and mother-specific variables of interest and control variables presented in Table 3.1. For father and mother-specific estimates, only families with at least one child who experienced paternal and maternal unemployment between ages zero and 16, respectively, are included. Indented variables are interactions with the previous non-indented variable. Controls represent the full set of control variables presented in Table 3.1 excluding sibling invariant controls. Fe, fixed effects. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.12

FE Regression Estimates of the Heterogeneous Effects of Paternal and Maternal Timing and Number of Years of Unemployment on Completed Years of Schooling by Addressing Reverse Causality

	Parents				Father				Mother			
	(1) Schooling	(2) Schooling	(3) Schooling	(4) Schooling	(5) Schooling	(6) Schooling	(7) Schooling	(8) Schooling	(9) Schooling	(10) Schooling	(11) Schooling	(12) Schooling
Years Unemployed (0-16)	0.096	0.103			0.163	0.467*			0.004	0.072		
	(0.120)	(0.149)			(0.217)	(0.218)			(0.133)	(0.172)		
Years Unemployed (0-4)			0.095	0.029			-0.028	0.351			0.138	0.078
			(0.164)	(0.225)			(0.261)	(0.287)			(0.208)	(0.259)
Years Unemployed (5-9)			0.147	0.242			0.219	0.552*			0.044	0.238
			(0.157)	(0.200)			(0.275)	(0.267)			(0.176)	(0.231)
Years Unemployed (10-16)			0.070	0.055			0.241	0.468*			-0.097	-0.013
			(0.136)	(0.163)			(0.221)	(0.227)			(0.172)	(0.209)
Parent Schooling High												
Years Unemployed (0-16)		-0.106				-0.981*				-0.136		
		(0.249)				(0.380)				(0.241)		
Years Unemployed (0-4)				0.004				-1.192*				0.089
				(0.334)				(0.492)				(0.374)
Years Unemployed (5-9)				-0.253				-1.009*				-0.473
				(0.309)				(0.472)				(0.332)
Years Unemployed (10-16)				-0.089				-0.657				-0.191
				(0.301)				(0.579)				(0.327)
Constant	12.889***	13.172***	12.847***	13.172***	13.021***	12.845***	12.984***	12.754***	13.534***	13.543***	13.330***	13.522***
	(1.013)	(1.115)	(1.024)	(1.138)	(1.137)	(1.107)	(1.166)	(1.142)	(1.134)	(1.133)	(1.130)	(1.098)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R-Squared	0.055	0.066	0.056	0.069	0.082	0.112	0.088	0.120	0.079	0.080	0.082	0.088
Observations	871	784	871	784	474	474	474	474	647	647	647	647

Notes. Estimates from within-family fixed effects with family-clustered standard errors. For father and mother-specific estimates, only families with at least one child who experienced paternal and maternal unemployment between ages zero and 16, respectively, are included. Years of unemployment when a child is of bad health and when there is a newborn aged zero or one in the family are excluded from (parent, father and mother-specific) *Years Unemployment* variables. An additional control variable for birth weight is added. Groups *Father* and *Mother* respectively include father and mother-specific variables of interest and control variables presented in Table 3.1. Indented variables are interactions with the previous non-indented variable. Controls represent the full set of control variables presented in Table 3.1 excluding sibling invariant controls. Fe, fixed effects. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.13

FE Regression Estimates of the Heterogeneous Effects of Paternal and Maternal Timing and Number of Years of Unemployment on College Attendance by Addressing Reverse Causality

	Parents				Father				Mother			
	(1) College	(2) College	(3) College	(4) College	(5) College	(6) College	(7) College	(8) College	(9) College	(10) College	(11) College	(12) College
Years Unemployed (0-16)	-0.022	-0.011			-0.027	-0.010			-0.040	-0.002		
	(0.028)	(0.041)			(0.045)	(0.058)			(0.035)	(0.048)		
Years Unemployed (0-4)			-0.029	-0.022			-0.032	-0.020			-0.066	-0.052
			(0.039)	(0.067)			(0.060)	(0.079)			(0.050)	(0.070)
Years Unemployed (5-9)			0.001	0.010			-0.030	-0.015			0.014	0.077
			(0.038)	(0.058)			(0.052)	(0.069)			(0.060)	(0.078)
Years Unemployed (10-16)			-0.031	-0.016			-0.023	-0.001			-0.044	-0.015
			(0.031)	(0.043)			(0.051)	(0.061)			(0.042)	(0.058)
Parent Schooling High												
Years Unemployed (0-16)		-0.046				-0.052				-0.075		
		(0.055)				(0.082)				(0.064)		
Years Unemployed (0-4)				-0.001				-0.016				-0.035
				(0.077)				(0.107)				(0.088)
Years Unemployed (5-9)				-0.053				-0.033				-0.150
				(0.072)				(0.091)				(0.102)
Years Unemployed (10-16)				-0.102				-0.120				-0.057
				(0.064)				(0.152)				(0.081)
Constant	0.867***	0.835**	0.854***	0.839**	0.686*	0.678*	0.687*	0.690*	1.125***	1.132***	1.119***	1.174***
	(0.244)	(0.263)	(0.249)	(0.268)	(0.295)	(0.298)	(0.294)	(0.294)	(0.262)	(0.263)	(0.279)	(0.285)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R-Squared	0.056	0.067	0.058	0.073	0.065	0.066	0.065	0.068	0.076	0.079	0.082	0.089
Observations	835	748	835	748	449	449	449	449	620	620	620	620

Notes. Estimates from within-family fixed effects with family-clustered standard errors. For father and mother-specific estimates, only families with at least one child who experienced paternal and maternal unemployment between ages zero and 16, respectively, are included. Years of unemployment when a child is of bad health and when there is a newborn aged zero or one in the family are excluded from (parent, father and mother-specific) *Years Unemployment* variables. An additional control variable for birth weight is added. Groups *Father* and *Mother* respectively include father and mother-specific variables of interest and control variables presented in Table 3.1. Indented variables are interactions with the previous non-indented variable. Controls represent the full set of control variables presented in Table 3.1 excluding sibling invariant controls. Fe, fixed effects. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.14

FE Regression Estimates of the Heterogeneous Effects of Paternal and Maternal Timing and Number of Years of Unemployment on Completed Years of Schooling by Addressing Layoffs Induced Measurement Error in Unemployment

	Parents				Father				Mother			
	(1) Schooling	(2) Schooling	(3) Schooling	(4) Schooling	(5) Schooling	(6) Schooling	(7) Schooling	(8) Schooling	(9) Schooling	(10) Schooling	(11) Schooling	(12) Schooling
Years Unemployed (0-16)	0.025 (0.105)	0.056 (0.129)			0.004 (0.182)	0.192 (0.190)			0.035 (0.109)	0.077 (0.149)		
Years Unemployed (0-4)			-0.007 (0.137)	0.020 (0.154)			-0.183 (0.207)	0.047 (0.226)			0.218 (0.175)	0.177 (0.184)
Years Unemployed (5-9)			0.146 (0.149)	0.207 (0.186)			0.250 (0.241)	0.504^{*} (0.243)			0.031 (0.159)	0.125 (0.233)
Years Unemployed (10-16)			-0.051 (0.131)	-0.038 (0.181)			0.098 (0.211)	0.227 (0.219)			-0.068 (0.156)	0.008 (0.219)
Parent Schooling High												
Years Unemployed (0-16)		-0.041 (0.266)				-0.619 (0.323)				-0.069 (0.197)		
Years Unemployed (0-4)				-0.038 (0.310)				-0.763 (0.444)				0.128 (0.349)
Years Unemployed (5-9)				-0.058 (0.372)				-0.767 (0.456)				-0.209 (0.338)
Years Unemployed (10-16)				0.023 (0.321)				-0.217 (0.585)				-0.107 (0.278)
Constant	12.749^{***} (1.003)	12.915^{***} (1.101)	12.677^{***} (1.003)	12.972^{***} (1.100)	13.353^{***} (1.166)	13.278^{***} (1.145)	13.039^{***} (1.197)	12.861^{***} (1.178)	12.913^{***} (1.164)	12.846^{***} (1.157)	12.582^{***} (1.134)	12.644^{***} (1.136)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R-Squared	0.058	0.069	0.065	0.081	0.079	0.105	0.108	0.143	0.085	0.090	0.092	0.102
Observations	871	784	871	784	474	474	474	474	647	647	647	647

Notes. Estimates from within-family fixed effects with family-clustered standard errors. *Years Unemployed* variable is split in two by excluding years of parental layoffs from years under parental unemployment and adding a new variable for years under parental layoffs. The new years under parental unemployment and years under parental layoffs variables are included in the regressions in an identical manner to the old years under parental unemployment variable (same age intervals, interactions and parent, father and mother-specific analyses). Both new variables are added to each regression, but years under parental layoffs are suppressed for spatial reasons (the same estimations presenting the effects of parental layoffs and suppressing parental unemployment can be found in Table A.15). Groups *Father* and *Mother* respectively include father and mother-specific variables of interest and control variables presented in Table 3.1. For father and mother-specific estimates, only families with at least one child who experienced paternal and maternal unemployment between ages zero and 16, respectively, are included. Controls represent the full set of control variables presented in Table 3.1 excluding sibling invariant controls. Indented variables are interactions with the previous non-indented variable. Fe, fixed effects. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.15

FE Regression Estimates of the Heterogeneous Effects of Paternal and Maternal Timing and Number of Layoffs on Completed Years of Schooling

	Parents				Father				Mother			
	(1) Schooling	(2) Schooling	(3) Schooling	(4) Schooling	(5) Schooling	(6) Schooling	(7) Schooling	(8) Schooling	(9) Schooling	(10) Schooling	(11) Schooling	(12) Schooling
Years Laid Off (0-16)	0.308	0.355			0.154	0.406			0.399	0.885*		
	(0.192)	(0.296)			(0.334)	(0.384)			(0.266)	(0.345)		
Years Laid Off (0-4)			0.303	0.213			0.049	0.360			0.359	0.799*
			(0.212)	(0.321)			(0.375)	(0.427)			(0.271)	(0.350)
Years Laid Off (5-9)			0.266	0.440			-0.053	0.171			0.614	1.099**
			(0.260)	(0.334)			(0.484)	(0.506)			(0.360)	(0.371)
Years Laid Off (10-16)			0.633	0.543			0.565	0.914			0.312	1.172
			(0.414)	(0.572)			(0.560)	(0.637)			(0.595)	(0.596)
Years Laid Off (0-16)		-0.174				-1.061*				-0.684		
		(0.376)				(0.508)				(0.423)		
Years Laid Off (0-4)				0.146				-1.198				-0.539
				(0.412)				(0.618)				(0.454)
Years Laid Off (5-9)				-0.731				-2.059				-0.621
				(0.526)				(1.244)				(0.642)
Years Laid Off (10-16)				-0.348				-1.764				-2.559*
				(0.890)				(1.078)				(1.134)
Constant	12.749***	12.915***	12.677***	12.972***	13.353***	13.278***	13.039***	12.861***	12.913***	12.846***	12.582***	12.644***
	(1.003)	(1.101)	(1.003)	(1.100)	(1.166)	(1.145)	(1.197)	(1.178)	(1.164)	(1.157)	(1.134)	(1.136)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R-Squared	0.058	0.069	0.065	0.081	0.079	0.105	0.108	0.143	0.085	0.090	0.092	0.102
Observations	871	784	871	784	474	474	474	474	647	647	647	647

Notes. Estimates from within-family fixed effects with family-clustered standard errors. *Years Unemployed* variable is split in two by excluding years of parental layoffs from years under parental unemployment and adding a new variable for years under parental layoffs. The new years under parental unemployment and years under parental layoffs variables are included in the regressions in an identical manner to the old years under parental unemployment variable (same age intervals, interactions and parent, father and mother-specific analyses). Both new variables are added to each regression, but years under parental unemployment are suppressed for spatial reasons (the same estimations presenting the effects of parental unemployment and suppressing parental layoffs can be found in Table A.14). Groups *Father* and *Mother* respectively include father and mother-specific variables of interest and control variables presented in Table 3.1. For father and mother-specific estimates, only families with at least one child who experienced paternal and maternal unemployment between ages zero and 16, respectively, are included. Controls represent the full set of control variables presented in Table 3.1 excluding sibling invariant controls. Indented variables are interactions with the previous non-indented variable. Fe, fixed effects. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.16

FE Regression Estimates of the Heterogeneous Effects of Paternal and Maternal Timing and Number of Years of Unemployment on College Attendance by Addressing Layoffs Induced Measurement Error in Unemployment

	Parents				Father				Mother			
	(1) Schooling	(2) Schooling	(3) Schooling	(4) Schooling	(5) Schooling	(6) Schooling	(7) Schooling	(8) Schooling	(9) Schooling	(10) Schooling	(11) Schooling	(12) Schooling
Years Unemployed (0-16)	-0.004	0.012			-0.022	-0.007			-0.002	0.029		
	(0.024)	(0.038)			(0.041)	(0.049)			(0.031)	(0.043)		
Years Unemployed (0-4)			0.005	0.033			-0.027	-0.004			0.011	0.036
			(0.035)	(0.053)			(0.056)	(0.067)			(0.047)	(0.061)
Years Unemployed (5-9)			0.011	0.021			-0.023	-0.003			0.030	0.071
			(0.032)	(0.052)			(0.051)	(0.064)			(0.049)	(0.071)
Years Unemployed (10-16)			-0.027	-0.022			-0.016	-0.004			-0.029	-0.006
			(0.029)	(0.049)			(0.048)	(0.055)			(0.038)	(0.061)
Parent Schooling High												
Years Unemployed (0-16)		-0.056				-0.027				-0.058		
		(0.050)				(0.080)				(0.051)		
Years Unemployed (0-4)				-0.041				-0.041				-0.052
				(0.063)				(0.121)				(0.076)
Years Unemployed (5-9)				-0.057				-0.029				-0.091
				(0.071)				(0.095)				(0.092)
Years Unemployed (10-16)				-0.082				-0.027				-0.037
				(0.065)				(0.138)				(0.073)
Constant	0.759**	0.703**	0.719**	0.671*	0.700*	0.706*	0.688*	0.671*	0.893**	0.872**	0.846**	0.868**
	(0.245)	(0.263)	(0.251)	(0.264)	(0.286)	(0.289)	(0.290)	(0.295)	(0.286)	(0.284)	(0.296)	(0.304)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R-Squared	0.056	0.076	0.059	0.084	0.066	0.079	0.067	0.083	0.078	0.087	0.087	0.097
Observations	835	748	835	748	449	449	449	449	620	620	620	620

Notes. Estimates from within-family fixed effects with family-clustered standard errors. *Years Unemployed* variable is split in two by excluding years of parental layoffs from years under parental unemployment and adding a new variable for years under parental layoffs. The new years under parental unemployment and years under parental layoffs variables are included in the regressions in an identical manner to the old years under parental unemployment variable (same age intervals, interactions and parent, father and mother-specific analyses). Both new variables are added to each regression, but years under parental layoffs are suppressed for spatial reasons (the same estimations presenting the effects of parental layoffs and suppressing parental unemployment can be found in Table A.15). Groups *Father* and *Mother* respectively include father and mother-specific variables of interest and control variables presented in Table 3.1. For father and mother-specific estimates, only families with at least one child who experienced paternal and maternal unemployment between ages zero and 16, respectively, are included. Controls represent the full set of control variables presented in Table 3.1 excluding sibling invariant controls. Indented variables are interactions with the previous non-indented variable. Fe, fixed effects. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.17

FE Regression Estimates of the Heterogeneous Effects of Paternal and Maternal Timing and Number of Layoffs on College Attendance

	Parents				Father				Mother			
	(1) Schooling	(2) Schooling	(3) Schooling	(4) Schooling	(5) Schooling	(6) Schooling	(7) Schooling	(8) Schooling	(9) Schooling	(10) Schooling	(11) Schooling	(12) Schooling
Years Laid Off (0-16)	0.045 (0.058)	0.159 (0.095)			-0.056 (0.106)	0.033 (0.121)			0.084 (0.075)	0.234* (0.118)		
Years Laid Off (0-4)			0.036 (0.063)	0.157 (0.113)			-0.070 (0.108)	0.037 (0.122)			0.051 (0.083)	0.162 (0.146)
Years Laid Off (5-9)			0.073 (0.082)	0.178 (0.111)			-0.056 (0.151)	0.011 (0.166)			0.165 (0.113)	0.305* (0.138)
Years Laid Off (10-16)			0.098 (0.111)	0.243 (0.169)			-0.016 (0.175)	0.121 (0.206)			0.249 (0.143)	0.398* (0.181)
Years Laid Off (0-16)		-0.176 (0.108)				-0.396 (0.226)				-0.211 (0.130)		
Years Laid Off (0-4)				-0.157 (0.126)				-0.350 (0.232)				-0.146 (0.161)
Years Laid Off (5-9)				-0.181 (0.133)				-0.270 (0.335)				-0.243 (0.165)
Years Laid Off (10-16)				-0.330 (0.206)				-0.541 (0.352)				-0.450* (0.196)
Constant	0.759** (0.245)	0.703** (0.263)	0.719** (0.251)	0.671* (0.264)	0.700* (0.286)	0.706* (0.289)	0.688* (0.290)	0.671* (0.295)	0.893** (0.286)	0.872** (0.284)	0.846** (0.296)	0.868** (0.304)
Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
R-Squared	0.056	0.076	0.059	0.084	0.066	0.079	0.067	0.083	0.078	0.087	0.087	0.097
Observations	835	748	835	748	449	449	449	449	620	620	620	620

Notes. Estimates from within-family fixed effects with family-clustered standard errors. *Years Unemployed* variable is split in two by excluding years of parental layoffs from years under parental unemployment and adding a new variable for years under parental layoffs. The new years under parental unemployment and years under parental layoffs variables are included in the regressions in an identical manner to the old years under parental unemployment variable (same age intervals, interactions and parent, father and mother-specific analyses). Both new variables are added to each regression, but years under parental unemployment are suppressed for spatial reasons (the same estimations presenting the effects of parental unemployment and suppressing parental layoffs can be found in Table A.14). Groups *Father* and *Mother* respectively include father and mother-specific variables of interest and control variables presented in Table 3.1. For father and mother-specific estimates, only families with at least one child who experienced paternal and maternal unemployment between ages zero and 16, respectively, are included. Controls represent the full set of control variables presented in Table 3.1 excluding sibling invariant controls. Indented variables are interactions with the previous non-indented variable. Fe, fixed effects. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

Table A.18

Probit Regressions for Identifying Selective Attrition in Reporting Fathers' and Mothers' Unemployment

	Father		Mother	
	(1) Unemployed	(2) Non-response	(3) Unemployed	(4) Non-response
Age	-0.013***	0.016***	-0.027***	0.029***
	(0.003)	(0.003)	(0.003)	(0.004)
Schooling	-0.107***	-0.102***	-0.090***	-0.177***
	(0.006)	(0.007)	(0.006)	(0.008)
Married	-0.467***	-3.720***	-0.423***	-2.965***
	(0.038)	(0.098)	(0.034)	(0.085)
Constant	0.399	1.329***	0.933**	2.692***
	(0.249)	(0.193)	(0.327)	(0.324)
Year FE	✓	✓	✓	✓
Observations	12922	15802	11436	12443

Notes. Employment statuses other than unemployed are excluded from the regressions. FE, fixed effects. Standard errors in parentheses. * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$.

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