Growing up with an Unemployed Mother*

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Abstract

We study the long-term effects of maternal unemployment on children's labor market outcomes. Children exposed to more maternal unemployment have lower wages and employment probabilities in adulthood. Importantly, these effects persist even after controlling for family income, indicating that increased parental time availability does not offset the scarring effects of unemployment. We find that the negative effects are concentrated among older children, suggesting that exposure to maternal unemployment during late schooling and early career years is particularly consequential. Specifically, we show that those children are more likely to drop out of high school, less likely to graduate from college, and more likely to select lower-return, lower-risk occupations in adulthood.

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JEL - Classification: E24, J62

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1 Introduction

Losing a job and subsequently being unemployed is a traumatic and costly experience for workers and their families. Unemployment has been shown to be associated with large and persistent declines in income and with mental health problems for workers, as well as lower educational attainment and worse labor outcomes for workers' children. Most of the harmful effects of parental job loss on children's labor outcomes have been documented by comparing displaced workers with non-displaced workers, who are otherwise similar. This approach, however, cannot distinguish the different effects of having an unemployed parent, such as lower household income, increased parental time availability, or psychological costs.

Most unemployment costs are typically attributed to income loss. However, research suggests that maternal care may be more beneficial for children than formal child care. This raises an important question: Could there be potential benefits for a child when a mother experiences unemployment and spends more time at home? In this paper, we investigate this question by measuring the long-term impact of maternal unemployment on children's labor market outcomes beyond the income loss effect and exploring the underlying mechanisms driving this impact.

To study the long-term effects of maternal unemployment, we construct a measure of children's exposure to maternal unemployment, which allows us to isolate the income loss effect from other potential effects of maternal unemployment. We find that the amount of time a mother spends unemployed when her child is growing up is negatively associated with a child's future employment probability and wage. Moreover, this negative relation is present even when controlling for family income, suggesting that the negative effect of unemployment goes beyond the decrease in income and that mothers' extra time at home does not mitigate it.

We conduct a comprehensive analysis to document the effect of having an unemployed mother on children's labor market outcomes. First, we demonstrate that our results do not just reflect unobservable factors that may correlate with the likelihood of the mother being unemployed, such as parental quality or innate skills of the mother. Second, we examine differential impacts across childhood stages and show that maternal unemployment is most detrimental in late adolescence, suggesting that early labor market behavior is an important channel explaining the results. We rationalize this fact by showing that higher exposure to maternal unemployment is associated with children having a higher probability of dropping out of high school, a lower probability of completing a college degree, and a tendency to work in lower-return, lower-risk occupations. In turn, we rationalize the lack of impact on young children by showing that deteriorating childcare quality is not as important by analyzing a broad set of variables, including children's test scores, mothers' time allocation, and family expenditures.

Our primary datasets are the National Longitudinal Survey of Youth 1979 cohort (NLSY79) and the NLSY79 Child and Young Adult cohort (NLSY79-CYA). Essential for our approach, the NLSY79 includes the labor force status of each respondent on a week-by-week basis, which allows us to construct the exposure of each child to his/her mother's unemployment when growing up. The NLSY79-CYA allows for intergenerational analysis since it follows the biological children of the women in the original 79 cohort from childhood and into adulthood, containing detailed information on all life stages of these children. We explore the labor market outcomes of these children when they are young adults and relate them to their mother's unemployment.

Children who spent more time with an unemployed mother when growing up have lower employment probability and lower future wages. In particular, a child who is one standard deviation above the mean exposure to maternal unemployment (approximately 67 additional childhood weeks with his/her mother unemployed) has a 4% lower future wage than the average child in the distribution. This negative return is approximately 30-50% of the return to one year of schooling, which is, on average, between 8 and 13% (Card, 1999). Interestingly, we do not find an impact of maternal unemployment on the number of hours worked.

Unemployment has two main effects. It reduces family income and increases parents' available time. We show that the former effect accounts only for a part of the negative impact of unemployment by controlling for the family income.[1] A child with one standard deviation above the mean exposure to maternal unemployment still displays a 3% lower future wage than the average child in the distribution with the same level of family income. This result suggests that maternal unemployment has scarring effects beyond lower income. Moreover, we show that this scarring effect of unemployment cannot be fully explained by children's education attainment, even though maternal unemployment does negatively affect it.

A possible concern is that mothers' work skills might be correlated with their parenting skills and innate abilities, and this correlation might generate the documented negative relation between children's exposure to maternal unemployment and their labor market outcomes. We show that this is not the case. First, we control for mothers' education levels, cognitive ability measures, and the time they spent unemployed outside of their child's first 18 years. The latter control serves as a placebo. If a mother's parenting ability is correlated with her likelihood of unemployment, this correlation should hold throughout her working life, not just during her child's childhood. Alternatively, if it is the child's exposure to the unemployment that generates the negative effect, then only the exposure during formative years should matter. We find that after accounting for these controls, most of the scarring effect of unemployment remains unexplained.

Second, we build on Caetano (2015), Caetano, Caetano, Fe, and Nielsen (2024a), Caetano, Cae-

[1] To account for this channel, we follow Carneiro and Heckman (2003) and construct a measure of family per capita permanent income, defined as the average discounted income flow to the family over the child's childhood.

tano, and Nielsen (2024b), and Caetano, Mansfield, and Slichter (2024d) to further show that our set of controls effectively captures most of the correlation between work and innate skills. Our sample has a marked bunching of children at zero maternal unemployment exposure. Therefore, we test whether there are significant differences between mothers with zero unemployment and those with short unemployment experiences. If exposure to maternal unemployment is the sole cause of the observed relationship, we should not see discontinuity in children's future wages or any other cofounder. However, if the unobservable variables play an important role in explaining the relationship, the discontinuity should be present. We show evidence of no discontinuity after accounting for our controls. This suggests that the correlation between work skills and parenting skills is not driving the negative relationship between maternal unemployment exposure and children's future labor market outcomes.

Our findings are robust to various alternative specifications and sensitivity checks. We show that the estimated effects of maternal unemployment are stable under different sample selection rules and after controlling for an extensive set of family background factors, prenatal conditions, and location-specific characteristics. We also test for potential nonlinearities and heterogeneous effects by gender and family structure. We also try to break non-employment into voluntary and involuntary components, with the latter including so-called "discouraged workers" or "hidden unemployment." To isolate the involuntary component, we instrument maternal non-employment using exposure to cyclical industries, exploiting the idea that job loss in these sectors is more likely driven by external aggregate shocks. The instrumented results yield a point estimate similar to our previous findings on unemployment, reinforcing the conclusion that a mother's inability to find work hurts children's prospects. Details of these robustness exercises are provided in the main text and appendix.

In the final section of the paper, we investigate the mechanisms underlying the scarring effect of maternal unemployment. We estimate how the effect of maternal unemployment depends on the stage of the childhood by breaking down the 18-year maternal unemployment exposure measure into six 3-year exposure measures. The impact of unemployment is predominantly concentrated in later childhood, with no significant impact observed for children under the age of 15. This suggests that the timing of maternal unemployment exposure plays a crucial role in shaping children's future labor market outcomes.

To understand why we do not find effects in early childhood, we examine maternal investments in children using data from the American Time Use Survey (ATUS), the Consumer Expenditure Survey (CE), and the NLSY. First, the ATUS data shows that unemployed mothers spend nearly twice as much time with their children compared to employed mothers. This additional time is reflected not only in total parent-child interaction but also in specific activities, such as helping with educational activities. Second, the CE data show that unemployed mothers spend significantly less on key children-related categories, particularly education and formal child care. This suggests a pattern of input substitution, where unemployed mothers compensate for reduced financial resources by increasing their direct time involvement with their children.

Supporting the input substitution hypothesis, we find that children exposed to maternal unemployment in their first five years do not perform worse on standardized tests by age 10. This lack of effect suggests that the additional parental time investment might be sufficient to offset the potential scarring effects of early childhood unemployment exposure.

To understand the mechanisms through which unemployment impacts older children, we look at children's educational attainment and occupation sorting. First, we find that higher exposure to maternal unemployment is associated with a greater probability of dropping out of high school and a lower probability of completing college. Second, we construct measures of the average return and riskness of each 3-digit occupation. We find that children with greater exposure to maternal unemployment tend to work in lower-return, lower-risk occupations as adults. These findings suggest that early labor market behavior is the key channel driving the long-term effects of maternal unemployment.

To summarize, we use a measure of childhood exposure to maternal unemployment to show that maternal unemployment has persistent negative effects on children's future labor market outcomes beyond the impact of household income loss. More broadly, our findings suggest that business cycles may have lasting, intergenerational consequences, particularly through their effects on older children. We show that parental unemployment, experienced during the teenage years, can shape early career decisions and risk preferences, ultimately impacting occupational choices in adulthood. Taken together, our results highlight the importance of distinguishing between the various channels through which parental unemployment affects children and emphasize the critical role of parental employment stability in shaping long-term economic prospects of their children.

Roadmap. Section 2 introduces our data sources and measurement strategy, detailing how we construct exposure to maternal unemployment and family permanent income. Section 3 describes our empirical approach. Section 4 presents our main findings, documenting the persistent negative effects of maternal unemployment on children's future wages and employment probabilities, along with robustness checks such as placebo regressions and bunching tests. Section 5 examines the underlying mechanisms, exploring how unemployment exposure at different childhood stages shapes the outcomes. Section 6 summarizes our contributions and discusses broader implications. Additional empirical results and robustness analyses are provided in the appendix.

Related Literature

Our paper contributes to two strands of literature: one that examines the consequences of job loss and unemployment, particularly the intergenerational effects, and another that studies the childhood determinants of long-run labor market outcomes, specifically the trade-off between parental time and income investment in child development.

It is well-established in the literature that workers experience persistent earnings losses after a job loss. This fact was documented by, for example, Jacobson, LaLonde, and Sullivan (1993) and Stevens (1997), and, more recently, Couch and Placzek (2010) and Raposo, Portugal, and Carneiro (2021). See Fallick (1996) and Kletzer (1998) for detailed literature reviews. Job loss has also been shown to impact other dimensions of workers' lives beyond earnings, such as health conditions (Schaller and Stevens, 2015; Cygan-Rehm, Kuehnle, and Oberfichtner, 2017) and even mortality (Sullivan and Von Wachter, 2009).

While most of this literature focuses on the direct impact on displaced workers, there is growing interest in the intergenerational consequences of job displacement. For examples, see Bratberg, Nilsen, and Vaage (2008), Oreopoulos, Page, and Stevens (2008), Hilger (2016), and Fradkin, Panier, and Tojerow (2019). Mixed evidence on the impact of parental jobs on children's labor market outcomes has been found. Oreopoulos et al. (2008) find that job loss leads to a decline in the future wages of displaced workers' children in Canada, with the effects being particularly pronounced at the lower end of the income distribution. However, they do not identify a specific mechanism driving this result. In contrast, Fradkin et al. (2019) find no significant impact of parental job displacement on children's wages in Belgium but document an increase in their labor supply— children of displaced workers tend to find jobs more quickly and work more at the beginning of their careers. Hilger (2016) finds no evidence that parental job loss affects children's earnings or college enrollment in the United States. Bratberg et al. (2008) finds similar results in Norway. Others have focused on the effects of parental job loss on children's non-labor market outcomes. For example, Coelli (2011), Lindo (2011), Rege, Telle, and Votruba (2011), and Stevens and Schaller (2011) find that parental displacement impacts birth weight, grade retention, and school performance.

Our paper makes two contributions to this discussion. First, it contributes by documenting how maternal unemployment, rather than previously considered general job displacement, affects children's long-term labor market outcomes. We use a specification that distinguishes between income loss and non-monetary channels to explain the link between parental unemployment and children's labor outcomes. Moreover, our measure captures the intensive margin of children's exposure to maternal unemployment, providing a different angle compared to the rest of the literature. Similar to the findings of Hilger (2016), we show that part of the negative effect of maternal unemployment is driven by selection on unobservables. However, we argue that selection alone does not fully explain the observed relationship, using placebo regressions and bunching tests (Caetano et al., 2024a). With the placebo regressions, we find no impact of unemployment exposure occurring before the child is born or after he/she turns 18. If a mother's latent parenting ability is correlated with her likelihood of unemployment, this correlation should persist throughout her working life and not just during her child's childhood. With the bunching test, we find no evidence of a discontinuity in future wages of children whose mothers experienced zero unemployment compared to those with small positive exposure. These results support our conclusion that the relationship between maternal unemployment and child outcomes is not solely driven by selection on mothers' unobserved characteristics.

Second, it contributes by documenting how the impact of maternal unemployment varies depending on the child's age. We document that most of the long-run impact of unemployment is driven by the effect on teenagers and is related to educational attainment and occupational sorting. We are the first to explore and document how the impact of unemployment differs over childhood stages in the U.S. Consistent with our findings, Carneiro, Salvanes, Willage, and Willén (2024) find that parents' job displacement that occurs in children's early adolescence matters more for their outcomes in Norway. They also show that family income is not the main driver of the effects. Uguccioni (2022) document how the impact of parental displacement differs depending on childhood stages in Canada and Bingley, Cappellari, and Ovidi (2024) in Demark.

Our study also relates to the broader literature on childhood determinants of long-run labor market outcomes. Various factors have been shown to shape future economic success. For instance, prior research has documented the role of family environment (Caucutt and Lochner, 2020; Pedtke, 2025), insurance coverage (Goodman-Bacon, 2021), teachers' quality (Chetty, Friedman, and Rockoff, 2014a), health conditions (Case, Fertig, and Paxson, 2005; Smith, 2009), and neighborhood effects (Chetty, Hendren, Kline, and Saez, 2014b; Chetty, Hendren, and Katz, 2016).

In particular, our study contributes to the literature on how parental income and time investment during childhood shape long-run labor market outcomes. Some studies examine this trade-off using natural experiments, such as tax credit expansions. For example, Bastian and Lochner (2022) find that the Earned Income Tax Credit (EITC) increases maternal labor supply but does not reduce time spent on educational activities with children. In contrast, Agostinelli and Sorrenti (2022) document that the EITC decreases the quality of mother-child interactions, particularly among disadvantaged families. Other studies also explore the effects of the EITC; for instance, Dahl and Lochner (2012, 2017) find positive effects on childhood test scores, while Bastian and Michelmore (2018) find positive effects on education and employment outcomes.

Beyond the EITC literature, several papers estimate the trade-off between maternal employment and childcare decisions. Bernal (2008) finds that maternal employment negatively affects children's cognitive abilities. Similarly, Baker, Gruber, and Milligan (2019) find negative effects on children's non-cognitive skills following Quebec's childcare expansion. More recently, Caetano, Caetano, Nielsen, and Sanfelice (2024c) use bunching methods and find that increased maternal labor supply negatively impacts children's early cognitive development. Lastly, the literature on maternity leave expansions provides mixed evidence. While Dustmann and Schönberg (2012) find no significant improvements in children's outcomes following maternity leave expansions in Germany, Carneiro, Løken, and Salvanes (2015) document positive effects in Norway.

Our paper contributes to this debate by showing that maternal unemployment does not generate a compensatory benefit through increased time with children for older children. We find that exposure to maternal unemployment leads to worse future labor market outcomes for the children even after controlling for family income. However, we find null results for young children, which suggests that the increased time with young children of unemployed mothers compensates for some of the negative effects of lower income.

Lastly, our paper is related to Blau and Grossberg (1992) and Krueger and Mueller (2012). Blau and Grossberg (1992) measure maternal time investment in children using the share of weeks mothers worked during their children's early years while controlling for family income to isolate the impact of labor supply from market inputs. Our study differs by focusing on the impact of unemployment exposure and considering the differential effects on children of different ages. Krueger and Mueller (2012) use data from the American Time Use Survey (ATUS) and the Survey of Unemployed Workers in New Jersey to analyze how unemployed workers allocate their time. In contrast, our study leverages ATUS to examine the time use allocation of unemployed mothers, with an emphasis on time spent with children.

2 Data and Measurement

We study the long-term effects on labor market outcomes of being exposed to maternal unemployment as a child. To do so, we use data that contains comprehensive information on mothers' labor market status and that tracks offspring as they enter the workforce. We construct a measure of a child's exposure to maternal unemployment, allowing us to use the variation across children in the amount of time their mothers were unemployed. This section will describe our dataset, methodology, and approach to addressing measurement challenges.

2.1 Data: The NLSY79 and NLSY79-CYA

We use data from two National Longitudinal Surveys.

First, we use the National Longitudinal Survey of Youth 1979 (NLSY79). The NLSY79 consists of a nationally representative sample of over 12,000 individuals ages 14-22 in 1979. The survey follows individuals longitudinally and has information about their employment, education, family background, and other life circumstances.

The NLSY79 keeps a detailed record of each respondent's employment, unemployment, and non-employment spells at a weekly frequency. It has records from January 1, 1978, to the last interview date. We use this labor force status array to construct our measure of a child's exposure to maternal unemployment, which will be described in the following subsection. The employment section of the NLSY79 also provides information on the characteristics of almost all the jobs the respondent ever had, including their usual earnings, industry, and workweek.

Second, we use data from the NLSY79 Child and Young Adult (NLSY79-CYA). The NLSY79-CYA has information on children born to women in the original NLSY79 cohort. These children were born between 1980 and 2016 and followed longitudinally from birth through adulthood. This dataset includes extensive information on these children, including cognitive, socioemotional, and physical development. It also includes information on their educational attainment, employment status, and earnings by following children into their young adulthood. The richness of the data allows us to explore how children's exposure to maternal unemployment affects their development, well-being, transition to adulthood, and, especially, long-term labor market outcomes.

In our analysis, we focus on the children of mothers from the original NLSY79 cohort who have reached working age. In the sample, we include young adults who are at least 21 years old and have a high school diploma or less or those who are at least 25 years old and have a college degree or higher. We have 6,861 young adults with at least one non-missing employment response. On average, they were observed 3.3 times, which yields a total of 22,920 respondent-year observations. Among the employed, 4,276 young adults have non-missing wage observations with an average of 2.03 observations per person – this gives 8,682 non-missing wage observations overall. We match each adult respondent with their mother. Appendix A includes a table with summary statistics and additional discussion related to sample creation.[2]

[2]We use the NLSY instead of the Panel Study of Income Dynamics (PSID) for two main reasons. First, the NLSY provides a detailed weekly array of labor market statuses, the key feature we rely on to create our unemployment exposure measure. The PSID measures unemployment by asking respondents how many weeks they were unemployed the previous year. Second, the NLSY offers detailed data on children's backgrounds during their childhood and their labor market outcomes in adulthood. This second reason may be less critical since the PSID includes two supplements, the Child Development Supplement (CDS) and the Transition into Adulthood Supplement (TAS), which could, in principle, allow similar analysis.

2.2 Constructing a Measure of Exposure to Maternal Unemployment

We measure children's exposure to maternal unemployment as the fraction of their childhood that their mothers spent unemployed. This measure captures the intensity of mothers' unemployment, differentiating someone who lost a job once and immediately found a new one versus someone who has been consistently unemployed. For example, a single and short spell means a small fraction of childhood spent with an unemployed mother, while long and multiple unemployment spells mean a large fraction. Previously, the literature has mainly looked at the effects of parental job loss using plant closures and mass layoffs in event study settings. Our approach complements the previous literature since it struggles to differentiate the effect of unemployment of different durations and to isolate the income loss effect from other potential effects of maternal unemployment.

To compute the fraction of children's childhood that their mothers spent unemployed, we explore the detailed labor force status array recorded in the NLSY79. It contains weekly information on the respondent's labor market status, whether "employed," "unemployed," "out of the labor force," or "on active military service." In the case of employment, it also recodes the respondent's primary job. In each interview, respondents are asked to report their labor market status for every week since their last interview, which means that the weekly data covers the entire time the respondent participated in the survey, even including years when they were not interviewed, and provides a comprehensive work history for each respondent.

More formally, we define the exposure of child i to his/her mother's unemployment as:

$$\textit{Exposure to Unemployed}_i = \frac{\sum_{\{t|age_{i,t}\in[0,18]\}} \mathbb{1}\{\textit{labor status}_{mother(i),t} = \text{unemployed}\}}{\sum_{\{t|age_{i,t}\in[0,18]\}} \mathbb{1}\{\textit{week}_{mother(i),t} = \text{observed}\}}. \tag{1}$$

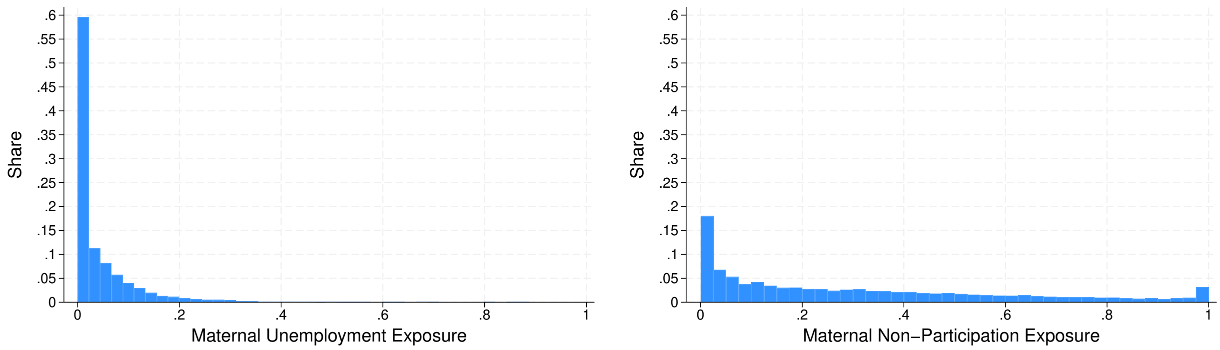
In the denominator, we count the number of weeks during which the mother reported being unemployed in the labor force status array. Here, *mother*(i) is a function that denotes the identifier of child i's mother, and *labor status*$_{mother(i),t}$ is a variable indicating her labor market status in week t. The summation is carried out over $\{t|age_{i,t} \in [0,18]\}$, which represents all the weeks t in which the child is between 0 and 18 years old. In the numerator, we count the number of weeks during which the mother's labor force status is observed. *week*$_{mother(i),t}$ is a variable that indicates whether the labor market status of the mother in week t is observed.[3]

[3]We implement our measure by first calculating maternal unemployment exposure for each year of a child's childhood. For instance, we count the unemployed weeks and the total observed weeks when the child was between the ages of 0 and 1, 1 and 2, and so on. Then, we compute the ratio between unemployed weeks and total observed weeks for each childhood year. We have a total of 206,436 child-year observations. We treat years with less or equal to 50 observed weeks as missing, which accounts for only 0.46% of child-year observations (948 observations). These observations are from children between 0 and 18 years old before 1978 and after 2018. The labor force status array has information since 1978; therefore, no information for years prior to that is available. Additionally, our sample only goes up to the 2019 release. As the last step, we average these ratios over the 18 years of childhood to construct a measure representing the exposure to maternal unemployment.

Following the same logic, we construct other exposure measures capturing the fraction of a child's childhood in which his/her mother was out of the labor force or employed. The three constructed measures of exposure sum to one by definition. Blau and Grossberg (1992) also use the share of weeks that mothers worked as a measure of the quantity of maternal time available to invest in children. However, unlike us, they do not look at different labor market statuses, particularly unemployment.

Figure 1 shows the distributions of exposures to mothers being unemployed and out of the labor force. There is much more variation in the out-of-the-labor-force exposure than in unemployment. During the first 18 years of their lives, young adults with at least one wage observation were, on average, exposed to 1 year of maternal unemployment, to 6.8 years of their mother being out of the labor force, and to 9.9 years of maternal employment. Standard deviations are 1.4 years for the exposure to unemployment, 5.3 years for the exposure to a mother being out of the labor force, and 5.6 years for the exposure to maternal employment. We use the bunching of mothers with zero unemployment to test for selection, following the ideas of Caetano (2015).

Figure 1: Fraction of Time in Each Labor Market State



Note: Maternal unemployment and non-participation exposures are defined as in equation (1) and can take values from 0 to 1. Each bar represents the share of young adults who were exposed to a particular level of maternal unemployment/non-participation during the first 18 years of their lives.

2.3 Measuring Family Permanent Income

Unemployment affects families through lower labor income and more available time. We create a measure of family income during a child's childhood to assess if unemployment affects children beyond income reduction.

More formally, we measure family income by constructing a discounted average of the family per capita income over the child's childhood. This measure was previously used by Carneiro and Heckman (2003), from whom we borrow the name *family permanent income*. The child i's family permanent income is defined as:

$$PI_i = \sum_{\{t|age_{i,t} \in [0,18]\}} \frac{Y_{i,t}}{(1+r)^t} \cdot \frac{\frac{1}{1+r} - 1}{(\frac{1}{1+r}^{19} - 1)} \,. \tag{2}$$

$Y_{i,t}$ is a measure of the per-capita income of i's family at time t. We use a constant interest rate, r, to express income in terms of the year the child was born.[4] Lastly, we sum income for all the child's childhood years and divide it by the sum of the discount factors to compute average income.

Our measure of per capita income is net family income divided by the family size. The BLS created the total net family income variable by summing different income sources for all household members. These include, for example, labor income as wages and salary, farm and business income, asset income, and government transfers. We manually create a family income measure for respondents for whom this variable is unavailable. The BLS also created the variable family size by counting the number of people who live in the household and are related to the respondent by blood, marriage, or adoption.[5] All values are expressed in \$10,000 in 1993 US Dollars, using the CPI. In our sample of young adults with non-missing wage observations, the average family permanent income is 0.865, with a standard deviation of 0.897.

Ideally, we would have the BLS's family income for each year of a child's childhood. However, this is not the case for two reasons. First, the NLSY began as an annual survey but transitioned to a bi-annual schedule after 1994. Therefore, by survey design, we do not observe family income for all the years of a child's childhood. Second, if a respondent misses a survey, he/she is not asked about income in the missed years. On average, we observe income for 10.17 years with a standard deviation of 4.03 years. In Section 3.2, we explain how we correct for measurement error in our results.

2.4 Dealing with Mothers' Unobserved Heterogeneity

To study the impact of maternal unemployment on children's labor market outcomes, we construct a measure of exposure to maternal unemployment. A concern is whether this measure captures both the effect of latent mothers' characteristics and the direct effect of unemployed mothers. In particular, maternal unemployment can be correlated with unobserved mothers' quality. Mothers who are worse at taking care and educating their children might also spend more time unemployed

[4]We calibrate $r = 0.05$, but our main results are robust to other values.

[5]When calculating family size, the BLS only counts family members related to the respondent by blood, marriage, or adoption. Foster relationships, partners, boarders, guardians, and others are not considered. Similarly, the income and earnings of spouses are included in the total family income, but those of partners are not. The reason for this choice, according to the BLS, is that inferring a financial relationship among individuals who are not legally related is more uncertain than inferring such a relationship among legal family members.

because of some cognitive and personal characteristics, e.g., innate ability, irresponsibility, absent-mindedness, etc.

In our analysis, we explore different quality proxies to address the unobserved quality issue. As we show in Subsection 4.3, none quantitatively change the documented negative impact of maternal unemployment on children. Bunching tests confirm this observation.

The first proxy for unobserved quality is mothers' education attainment. The assumption is that the more educated a mother is, the better she is at educating her children and less likely to experience unemployment. The second proxy is mothers' performance on the Armed Forces Qualification Test (AFQT), which is used in the literature as a measure of ability. Again, the assumption is that mothers with a high AFQT score are better at educating their children and less likely to experience unemployment. So, by also controlling for mothers' education and their AFQT score and comparing the results without it, we can better understand the role of unobserved quality in mothers' care.

Our last approach is to look at the total amount of time the mother spent unemployed in her entire adult lifetime. The assumption is that if mothers' ability to invest in their children's human capital is correlated with their likelihood of being unemployed, this correlation holds for their entire working life and not only during the child's childhood. So, we measure the time a mother spent unemployed between the ages of 25-60, but we exclude the 18 years of her child's childhood. This measure cannot account for the negative association between maternal unemployment and children's labor market outcome.

3 Empirical Strategy

In this section we introduce our empirical strategy that allows us to document the association between mothers' unemployment and their children's long-term outcomes, and discuss the potential issues. For the ease of the interpretation, we use linear models for our main analysis. However, in Appendix B.2 we examine whether the effects of maternal non-employment are in fact non-linear.

3.1 Estimating the Impact of Maternal Unemployment on Children's Labor Market Outcomes

We evaluate the effect of exposure to maternal unemployment by projecting labor market outcomes of young adult i at time t, y_{it}, on our measures of maternal unemployment and out-of-the-labor force exposures, UNEMP_i and OLF_i. We estimate the following equation:

$$y_{it} = \alpha + \beta_1 \mathit{UNEMP}_i + \beta_2 \mathit{OLF}_i + \beta_3 \mathit{PI}_i + \gamma_1 X_i + \gamma_2 Z_{it} + \epsilon_{it} \; . \tag{3}$$

y_{it} stands for the labor market outcome of the young adult. UNEMP_i and OLF_i represent the measure of exposures. PI_i represents permanent income, calculated using equation (2). X_i and Z_{it} include controls. ϵ_{it} is a residual. Carneiro and Heckman (2003), Caucutt and Lochner (2020), and others used similar regressions to show that family permanent income predicts children's future educational attainment.

It is important to clarify the timing of the variables. The labor market outcome, y_{it}, is measured when the child is already of working age. For those with a high school degree or less, this would be older than 21 years, and for those with a college degree, it would be older than 25 years. The exposure measures, UNEMP_i and OLF_i, as well as the permanent income measure, PI_i, are calculated when the child is younger than 18 years old. Essentially, equation (3) is a forecasting exercise, where measures obtained when the child was younger than 18 years old are used to predict future outcomes.

We analyze a set of labor market outcomes. In particular, we test the impact on the logarithm of total earnings, the logarithm of wages, and the logarithm of hours worked. We also use indicator functions to capture other discrete choices of these young adults, such as education and labor force participation.

Time-invariant child-specific controls, X_i, include race, sex, and mother's characteristics, such as her education, cognitive test scores, marital history, and spouse's characteristics. Time-variant controls, Z_{it}, capture a cubic polynomial in child's current age and time-fixed effects. For variables observed more than once during a child i's childhood, we use the mode to aggregate categorical variables such as marital status and the mean to aggregate continuous variables such as spouses' workweek.

We estimate equation (3) using ordinary least squares. Our identifying assumption is that the error term is independent of the exposure measures after conditioning on the control variables. This assumption might be violated for two reasons. First, maternal unemployment might be correlated with unobserved mothers' quality in investing in children's human capital. We deal with it by including controls that correlate mothers' latent abilities and using bunching tests to determine how good these proxies are. Second, maternal unemployment might be correlated with the latent permanent income measured without error, which we tackle by instrumenting permanent income. The following subsection explains our instrument.

3.2 Addressing Measurement Error

As mentioned above, the measurement error in family permanent income is a concern for our analysis.[6] To deal with it, we use as an instrument an alternative measure of permanent income constructed using a different set of information available in the NLSY. First, we construct a weekly earnings series for each respondent using the labor market status array. Weekly earnings are defined as the workweek times the wage rate at the primary employment. Then, we aggregate weekly earnings into an annual earnings measure and construct the family's permanent income as in equation (2).

Our instrument addresses the issue of not observing mothers' family income in all the years. That is because we use the labor market array, which covers the entire participation time of a respondent in the survey, even including the years she was not interviewed. However, it only captures labor income and does not account for other sources of income, such as asset and business income, and spouses' income. We address this by interacting our instrument with dummies that capture mothers' marital status and whether she is the household's primary earner. Note that, when using the instrument, the dummies capturing mothers' marital and primary earner statuses are included in the main regression to control for their direct effect on children's outcomes. Only the interactions between these variables are excluded from the main regression.

When dealing with measurement error, we estimate equation (3) using two-stage least squares and the alternative permanent income measure as the instrument. First, the relevance assumption is satisfied by construction: permanent income and its alternative measure capture the same concept but use different variables in their construction. Second, the exogeneity assumption is satisfied if the error term in equation (3) is uncorrelated with the instrument. This requires that both the measurement error in permanent income and unobserved mothers' abilities are uncorrelated with the alternative permanent income measure. We deal with the latter by including controls that correlate with mothers' latent abilities.

4 Main Results

We document the long-run impact of exposure to maternal unemployment on children's labor market outcomes. In particular, our results show that children who were more exposed to maternal unemployment have lower wages and a lower likelihood of being employed. These negative rela-

[6]Family permanent income is subject to measurement error. First, survey data on income is well known to be noisy. Second, we do not observe family income for each year of the child's childhood. Thus, the average family permanent income is computed from only a subset of years. On the other hand, our measure of exposure to maternal unemployment is less likely to be subject to measurement error since it is constructed using the labor market status array. The NLSY spends significant time constructing those and ensuring their quality.

tions are robust to controlling for proxies that correlate with mothers' unobserved heterogeneity and accounting for measurement error.

4.1 Effects on Labor Market Outcomes

First, we estimate equation (3) without including permanent income to document the full impact of maternal labor status on the labor market outcomes of their children. We look at the effects on total earnings, wages, workweek, and employment probability. In Appendix B, we also show results for a measure of occupation risk.

In Table 1, Column 1, we document that children whose mothers spent more time unemployed or out of the labor force during their childhood had lower earnings in their adulthood. The estimated coefficient on the unemployment exposure measure is -0.66 (standard deviation 0.15) and on the labor-force participation exposure measure is -0.32 (standard deviation 0.04). For the magnitude of the effect, a child whose exposure to maternal unemployment was 1 standard deviation above the mean had, on average, 5% lower earnings. In the case of labor-force participation exposure, a 1 standard deviation above the mean is associated with 9% lower earnings.

In Columns 2 and 3, we show that the decline in earnings comes mainly from a decline in wages and not a decline in the workweek. The estimated coefficients on the unemployment and labor-force participation exposure measures on wages are -0.50 (standard deviation 0.09) and -0.16 (standard deviation 0.02), respectively. A 1 standard deviation higher exposure to maternal unemployment is associated with 4% lower wages, while the association with hours is positive but statistically insignificant. Higher exposure to maternal labor-force non-participation is associated with lower wages and hours.

We focus on young adults who were employed during the survey week in Columns 1-3, while, in Column 4, we look at the sample of young adults who reported any employment status. Notice that the sample size is 2.5 times bigger in Column 4 than in Columns 1-3. While 70% of those in Column 4 are employed, only half of them reported information about wages and hours. We document that those who are more exposed to maternal non-employment are less likely to be employed. Notice that the effects of being out of the labor force and being unemployed are pretty similar in their effects on the employment probability. So, while the impact of the exposure measures on the intensive margin of labor supply is small, their impact on the extensive margin is large and significant.

In Appendix B, Tables B10 and B11 show that greater maternal unemployment exposure during childhood is associated with lower occupational earning risk in adulthood, consistent with individuals self-selecting into safer but lower-earning occupations. The effect is more pronounced for

Table 1: The Impact of Mother's Labor Market Status on Child's Outcomes

	(1) log(total earn.)	(2) log(wage)	(3) log(wkly hours)	(4) employed
OLF	-0.321**	-0.161**	-0.035**	-0.226**
	(0.038)	(0.021)	(0.009)	(0.015)
UNEMP	-0.664**	-0.500**	0.035	-0.340**
	(0.152)	(0.085)	(0.034)	(0.065)
Observations	8,683	8,683	8,683	22,920
R2	0.167	0.167	0.060	0.067

Note: OLF and UNEMP are our exposure measures to maternal labor-force non-participation and unemployment, respectively. See equation (1) for construction details. Controls include dummy variables for children's race and gender, a cubic polynomial in children's age, and fixed effects for the survey year. All models are estimated by ordinary least squares. Standard errors are clustered at the children's level and reported in parentheses.
* and ** indicate statistically significant at the 10% and 5% levels.

individuals over 30 years old, likely because older workers have had more time to transition into occupations that better match their risk preferences acquired from childhood experiences. Since job search and career changes take time, the impact of early-life factors on occupational sorting strengthens as workers age. This finding aligns with Hegarty (2022), who documents a similar mechanism using the Panel Study of Income Dynamics (PSID).

4.2 Beyond Income: The Scarring Effects of Maternal Unemployment

Maternal unemployment can impact child outcomes by decreasing family income and, consequently, affecting parents' investment in the child's human capital. To separate the time and income channels of unemployment, we estimate equation (3) again, but now controlling for the household permanent income. We restrict ourselves to analyzing the impact of exposure to maternal unemployment and labor market participation on children's wages and employment probability since the other labor market outcomes were insignificant in the previous table.

Maternal unemployment and labor-market participation have long-run negative impacts on children, even after controlling for family income. Table 2, Columns 2 and 4 show the impact on wages and employment probability, respectively. Even after controlling for family income, children exposed to more maternal unemployment or lower labor-market participation have lower wages and lower employment probability. The estimated impacts are almost unchanged from the baseline results, decreasing between 31% and 9% after controlling for family income. Columns 1 and 3 reproduce the results without controlling for family income for comparison.

It could be that maternal unemployment has a negative impact on children's outcomes, controlling for permanent income, because the family income is measured with error and unemployment is correlated with the latent true permanent income. We deal with it by estimating equation (3) by two-stage least squares and using an alternative measure of permanent income constructed using a different set of questions in the NLSY. We interact our instrument with dummies that capture whether the mother is the household's primary earner and whether she is married. These dummies are included in the main regression to control for their direct effect on children's outcomes, and only the interactions between these variables are excluded from the main regression. More details are provided in Subsection 3.2.

Table 2, Column 3 shows that the impact of permanent income on wages increases from 0.099 to 0.154 when corrected for measurement error. This coefficient implies that each $10,000 increase in average family income when children are growing up increases their future wages by 0.154 log points. Column 6 shows that the same is true for the impact on employment probability, with each $10,000 increase in family income increasing their employment probability by 4.7 percentage points. After controlling for permanent income and correcting for measurement error, the estimated effects of exposure to maternal unemployment and labor-market non-participation decrease relative to the OLS results but remain negative and significant. Contrasting the magnitude of the estimated coefficient of unemployment exposure and permanent income, one standard deviation more exposure to unemployment is similar to having a $1,794 lower average family income when growing up.

Carneiro and Heckman (2003), Caucutt and Lochner (2020), and others have shown that family income predicts children's educational attainment. They do it by regressing educational attainment dummies on average family income. In Table 3, we perform the same exercise as they did but also allow our exposure measures to enter the specification and instrument for measurement error in permanent income, as in Table 2. Our estimated coefficients on permanent income, which are similar to the ones reported by Caucutt and Lochner (2020), suggest that permanent income reduces the likelihood of a child dropping out of high school while increasing their chances of attending and graduating from college.

Interestingly, we find that, conditional on permanent income, higher exposure to maternal unemployment and labor-force participation increases the likelihood of a child dropping out of high school while decreasing their chances of attending and graduating from college. In monetary terms, one standard deviation more exposure to unemployment decreases the likelihood of graduating from college by 1.13%. This effect is similar to having a $3,750 lower average family income when growing up.

Since higher exposure to maternal unemployment and labor-force participation impacts educational attainment, we investigate how much of documented scaring effects on wages and employment come through the education channel. For that, we estimate our equation (3), now controlling

Table 2: The Impact on Child's Outcomes After Controlling for Family Income

	OLS		IV	OLS		IV
	(1)	(2)	(3)	(4)	(5)	(6)
	log(wage)	log(wage)	log(wage)	emp.	emp.	emp.
OLF	-0.176**	-0.123**	-0.103**	-0.201**	-0.184**	-0.189**
	(0.024)	(0.024)	(0.026)	(0.017)	(0.017)	(0.018)
UNEMP	-0.393**	-0.329**	-0.305**	-0.303**	-0.275**	-0.284**
	(0.085)	(0.078)	(0.078)	(0.068)	(0.067)	(0.068)
Permanent Income		0.099**	0.136**		0.032**	0.022*
		(0.010)	(0.021)		(0.006)	(0.012)
F statistic			59.500			104.215
Observations	8,378	8,378	8,378	21,737	21,737	21,737
R2	0.175	0.196	0.193	0.065	0.067	0.066

Note: OLF and UNEMP are our exposure measures to maternal labor-force non-participation and unemployment, respectively. See equation (1) for construction details. Permanent Income is in $10,000s (discounted present value) as of birth year. See equation (2) for construction details. Controls include dummy variables for children's race and gender, a cubic polynomial in children's age, dummy variables for mothers' marital and primary earner statuses, and fixed effects for the survey year. Columns 1, 2, 4, and 5 are estimated by ordinary least squares. Columns 3 and 6 are estimated by two-stage least squares. Excluded instruments are the alternative permanent income measure and its interactions with dummy variables for mothers' marital and primary earner statuses. Standard errors are clustered at the children's level and reported in parentheses. The F statistic is the Kleibergen-Paap F statistic.
* and ** indicate statistically significant at the 10% and 5% levels.

for education attainment dummies. Table 4, Columns 2 and 4 present the results, while Columns 1 and 3 reproduce the results only controlling for permanent income. After controlling for education attainment, the coefficients decrease between 22% and 49%, implying that the scarring effects of unemployment and labor-market participation go beyond their impact on education attainment.

Table 3: The Impact on Education Attainment

	(1) HS dropout (ages 21–24)	(2) Attended college (ages 24–27)	(3) Graduated college (ages 24–27)
OLF	0.124**	-0.165**	-0.057**
	(0.038)	(0.021)	(0.013)
UNEMP	0.340**	-0.395**	-0.145**
	(0.128)	(0.073)	(0.047)
Permanent Income	-0.075**	0.072**	0.037**
	(0.034)	(0.017)	(0.011)
F statistic	55.555	89.597	89.597
Observations	3,516	7,719	7,719
R2	0.306	0.257	0.368

Note: The dependent variables are indicator variables derived from the respondent's highest grade completed at the survey date. OLF and UNEMP are our exposure measures to maternal labor-force non-participation and unemployment, respectively. See equation (1) for construction details. Permanent Income is in $10,000s (discounted present value) as of birth year. See equation (2) for construction details. Controls include dummy variables for children's race and gender, a cubic polynomial in children's age, dummy variables for mothers' marital and primary earner statuses, and fixed effects for the survey year. All models are estimated by two-stage least squares. Excluded instruments are the alternative permanent income measure and its interactions with dummy variables for mothers' marital and primary earner statuses. Standard errors are clustered at the children's level and reported in parentheses. The F statistic is the Kleibergen-Paap F statistic.

* and ** indicate statistically significant at the 10% and 5% levels.

Table 4: The Impact After Controlling for Family Income and Education Attainment

	(1) log(wage)	(2) log(wage)	(3) emp.	(4) emp.
OLF	-0.100**	-0.054**	-0.187**	-0.145**
	(0.026)	(0.025)	(0.019)	(0.018)
UNEMP	-0.322**	-0.243**	-0.299**	-0.216**
	(0.081)	(0.073)	(0.068)	(0.067)
Permanent Income	0.137**	0.115**	0.023*	0.008
	(0.022)	(0.021)	(0.012)	(0.012)
High School		0.026*		0.076**
		(0.015)		(0.012)
Some College		0.174**		0.173**
		(0.017)		(0.012)
College or more		0.359**		0.248**
		(0.021)		(0.014)
F statistic	58.371	56.465	102.777	100.833
Observations	8,017	8,017	20,857	20,857
R2	0.187	0.261	0.065	0.091

Note: OLF and UNEMP are our exposure measures to maternal labor-force non-participation and unemployment, respectively. See equation (1) for construction details. Permanent Income is in $10,000s (discounted present value) as of birth year. See equation (2) for construction details. Controls include dummy variables for children's race, gender, and educational attainment, a cubic polynomial in children's age, dummy variables for mothers' marital and primary earner statuses, and fixed effects for the survey year. All models are estimated by two-stage least squares. Excluded instruments are the alternative permanent income measure and its interactions with dummy variables for mothers' marital and primary earner statuses. Standard errors are clustered at the children's level and reported in parentheses. The F statistic is the Kleibergen-Paap F statistic.
* and ** indicate statistically significant at the 10% and 5% levels.

4.3 Accounting for Mothers' Unobserved Heterogeneity

We documented that the scarring effects of unemployment and non-participation go beyond their impact on family income and children's education. Potentially, this scarring effect can be explained by unobserved mothers' heterogeneity, such as in their ability to invest in their children's human capital. For example, if mothers who are bad at taking care and educating their children are also the ones who spend more time unemployed or out of the labor force, our exposure measures might be capturing the effect of latent mothers' characteristics and not the direct effect of the market status. In this subsection, we argue that latent characteristics are not the explanation.

In Table 5, we control for three proxies that capture mothers' abilities to invest in children's human capital: (1) mothers' education attainment, (2) cognitive test scores, and (3) time spent unemployed outside of the first 18 years of her child. Blau and Grossberg (1992) use similar variables to control for the quality of parental time in their work. Columns 2-4 gradually introduce these proxies of mothers' abilities as controls. For comparison, Column 1 reports the results without any proxy.

Table 5: Measures of Mother's Ability: Effects on Wages and Employment

	(1) log(wage)	(2) log(wage)	(3) log(wage)	(4) log(wage)	(5) emp.
OLF	-0.055**	-0.041	-0.036	-0.035	-0.132**
	(0.025)	(0.026)	(0.026)	(0.026)	(0.019)
UNEMP	-0.266**	-0.252**	-0.229**	-0.212**	-0.137*
	(0.073)	(0.073)	(0.073)	(0.078)	(0.070)
Permanent Income	0.115**	0.107**	0.102**	0.102**	0.008
	(0.022)	(0.024)	(0.024)	(0.024)	(0.014)
Educ Dummies	Yes	Yes	Yes	Yes	Yes
Mom Educ Dummies		Yes	Yes	Yes	Yes
Mom AFQT			Yes	Yes	Yes
Remaining Unemp				Yes	Yes
F statistic	58.868	51.283	49.798	49.977	77.825
Observations	7,710	7,710	7,710	7,710	20,102
R2	0.268	0.270	0.273	0.273	0.094

Note: OLF and UNEMP are our exposure measures to maternal labor-force non-participation and unemployment, respectively. See equation (1) for construction details. Permanent Income is in $10,000s (discounted present value) as of birth year. See equation (2) for construction details. Column 1 only has the baseline controls, while other columns have additional controls. Column 2 includes mother's education attainment dummies. Column 3 additionally controls for mothers' Armed Forces Qualification Test (AFQT) scores. We include the test scores as quantiles of the score distribution. Column 4 also includes the mother's time spent unemployed between ages 25-60, excluding the first 18 years of the child's life. This control captures unobservable characteristics that cannot be captured by education achievements or cognitive test scores. Baseline controls include dummy variables for children's race, gender, and educational attainment, a cubic polynomial in children's age, dummy variables for mothers' marital and primary earner statuses, and fixed effects for the survey year. All models are estimated by two-stage least squares. Excluded instruments are the alternative permanent income measure and its interactions with dummy variables for mothers' marital and primary earner statuses. Standard errors are clustered at the children's level and reported in parentheses. The F statistic is the Kleibergen-Paap F statistic.
* and ** indicate statistically significant at the 10% and 5% levels.

Looking across Columns 2 to 4, we can see that our proxies of ability explain only a small portion of the negative effect on wages associated with exposure to unemployment. For example, when controlling for all proxies in Column 4, we find that one standard deviation higher exposure is associated with -1.5% lower wages. Similarly, our proxies explain a small portion of the effect associated with exposure to lower labor-market participation. The decrease in the effect is sufficient to make the impact of exposure to labor-market participation statistically insignificant. Overall, a significant portion of the long-term negative impact of unemployment on children's prospects is still not accounted for. In the case of the negative effect of non-participation, a significant fraction can be explained by our proxies and other controls.

In Table 5, Column 5, we present the relation between the exposure to maternal unemployment and labor-force participation and a child's employment probability when controlling for our three proxies of mothers' abilities. Overall, the proxies and other controls explain only a small part of the effect of unemployment and labor-force participation.

Appendix B has additional results. Table B3 controls for the other family characteristics a child faced growing up. In particular, we control for the mother's age at childbirth, spousal labor supply, family structure, location, and grandmother's presence. The estimated impact of maternal unemployment on adult wages increases after adding the full set of controls. The last set of controls accounts for the fact that extended family members influence the college attendance probabilities and test scores of their younger relatives (Loury, 2006).

4.4 Placebo Tests

The critical assumption in our analysis is that the mothers' labor-market statuses, especially unemployment, are driven by exogenous factors and not by an unobservable heterogeneity. As an additional test, we do a placebo test by controlling for exposure to maternal unemployment that happens when children are already in adulthood and before their birth. In particular, if mothers' ability to invest in their children's human capital is correlated with their likelihood of being unemployed, this correlation holds for their entire working life and not only during the child's childhood. A reassuring result is that these extra exposure measures are uncorrelated with children's wages. These results reinforce our interpretation that there is something specific in the fact that mothers cannot find work during their children's childhood that hurts children's future prospects.

In particular, we control, in Table 6, for maternal labor-market statuses when children are already in adulthood, between the ages of 25 and 30, and before they are born, 5 years before birth to one month before birth. In Column 1, we report the baseline result of Table 5, Column 5, for reference. Column 2 shows that controlling for maternal unemployment when their children are already in adulthood does not impact the estimated scarring effect of unemployment exposure during childhood. Column 3 shows that the same is true when controlling for maternal unemployment before the children are born. Column 4 shows the result, including both measures. Column 5 shows that the results of exposure to maternal labor-market non-participation are statistically insignificant in all specifications.

Table 6: Placebo test

	(1) log(wage)	(2) log(wage)	(3) log(wage)	(4) log(wage)	(5) emp.
OLF when child is bw 0-18	-0.036	-0.027	0.032	0.041	-0.090**
	(0.026)	(0.027)	(0.032)	(0.034)	(0.024)
OLF when child is bw 25-30		-0.018		-0.012	-0.030*
		(0.018)		(0.024)	(0.018)
OLF when child is bw -5-0			-0.041	-0.042	-0.001
			(0.027)	(0.027)	(0.021)
UNEMP when child is bw 0-18	-0.229**	-0.217**	-0.220**	-0.211**	-0.081
	(0.073)	(0.075)	(0.101)	(0.105)	(0.091)
UNEMP when child is bw 25-30		-0.027		-0.012	-0.078
		(0.053)		(0.068)	(0.061)
UNEMP when child is bw -5-0			0.051	0.048	-0.031
			(0.076)	(0.076)	(0.054)
Permanent Income	0.102**	0.104**	0.066**	0.067**	0.017
	(0.024)	(0.025)	(0.023)	(0.023)	(0.016)
Educ Dummies	Yes	Yes	Yes	Yes	Yes
Mom Educ Dummies	Yes	Yes	Yes	Yes	Yes
Mom Controls	Yes	Yes	Yes	Yes	Yes
F statistic	49.798	47.798	39.012	36.957	58.601
Observations	7,710	7,670	4,162	4,122	11,489
R2	0.273	0.272	0.292	0.292	0.106

Note: OLF and UNEMP are our exposure measures to maternal labor-force non-participation and unemployment, respectively. See equation (1) for construction details. Permanent Income is in $10,000s (discounted present value) as of birth year. See equation (2) for construction details. Controls include dummy variables for children's race, gender, and educational attainment, a cubic polynomial in children's age, dummy variables for mothers' marital and primary earner statuses, mothers' ability controls, and fixed effects for the survey year. For mothers' ability, we use mothers' education attainment dummies and mothers' Armed Forces Qualification Test (AFQT) scores, which we include as quantiles. We do not include the mother's time spent unemployed between ages 25-60, excluding the first 18 years of the child's life. This variable is extremely correlated with our placebo measures. All models are estimated by two-stage least squares. Excluded instruments are the alternative permanent income measure and its interactions with dummy variables for mothers' marital and primary earner statuses. Standard errors are clustered at the children's level and reported in parentheses. The F statistic is the Kleibergen-Paap F statistic.
* and ** indicate statistically significant at the 10% and 5% levels.

4.5 Bunching Tests and Selection Concerns

In the last two sections, we used proxies for mothers' abilities and placebo tests to argue that those abilities do not simultaneously affect mothers' likelihood of unemployment and child outcomes. Instead, we argue that exogenous factors drive maternal unemployment. As an additional test to empirically validate this exogeneity assumption, we employ a bunching test at the point of zero unemployment. Intuitively, mothers with short unemployment spells should have similar observable and unobservable characteristics to those with no unemployment if the assignment is quasi-random. Thus, examining observables around the zero-unemployment threshold serves as an indirect test for endogeneity (Caetano, 2015; Caetano et al., 2024a). Details on the implementation are given in the figure note.

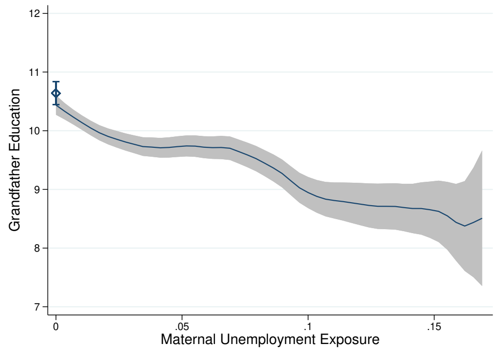
We first implement this test graphically using local linear regressions. First, we regress children's wages against exposure to maternal unemployment. Second, we regress maternal grandfather's education against exposure to maternal unemployment to detect spurious correlations induced by endogeneity. In particular, the grandfather's education is a placebo outcome that should not be affected by maternal unemployment. Figure 2, Panels (a) and (b) show that, without controls, the placebo outcome mirrors the general pattern of children's wages, raising initial concerns about selection bias. The graphical analysis also reveals discontinuities around the zero unemployment threshold.

However, Figure 2, Panels (c) and (d) show that after including the proxies for mother ability and other controls, the grandfather's education shows a positive relationship with maternal unemployment exposure up to 1.8 years of exposure (21 months). After that, it turns slightly negative. Crucially, despite controlling for these observable characteristics, maternal unemployment continues to negatively affect children's labor market outcomes in all ranges of the exposure measure. Moreover, the graphical analysis reveals no discontinuities around the zero unemployment threshold. This evidence should alleviate concerns about the negative impact of maternal unemployment being driven by endogeneity.

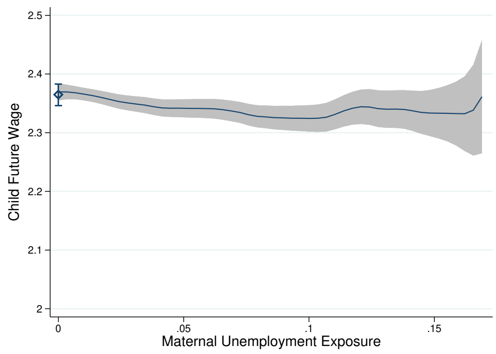
Ideally, the placebo outcome, the grandfather's education, would be unrelated to exposure to maternal unemployment after accounting for our controls. The fact that, in Figure 2, Panel (d), the grandfather's education is low for exposure to maternal unemployment higher than 1.8 years (21 months) raises the question of whether these tail events are driving the results. In Table 7, we reestimate our model restricting the upper part of the distribution. Column 1 shows the full sample, while Columns 2, 3, and 4 restrict the sample to observations below percentiles 95, 90, and 85, respectively. If something, the coefficient on the exposure measure of unemployment increases when restricting the sample, implying that tail events are not driving the results.

Figure 2: Bunching Test: Outcome and Placebo Outcome

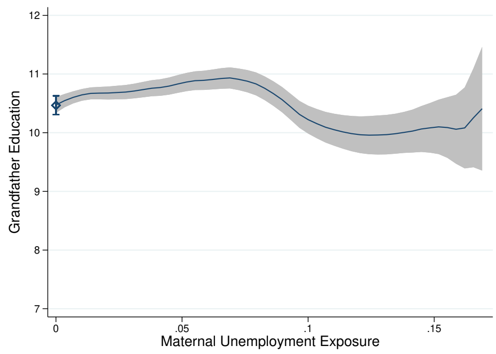
(a) Child Wage



(b) Grandfather's Education



(c) Residualized Child Wage



(d) Residualized Grandfather's Education

Note: This figure presents the bunching test results for both the primary outcome variable (Child Wage) and a placebo outcome (Grandfather's Education). Panels (a) and (b) show raw outcomes, while Panels (c) and (d) display residualized outcomes, controlling for relevant covariates. To compute residualized outcomes, we regress the relevant variable on maternal unemployment exposure and a full set of controls, including child race, sex, age, year-fixed effects, education dummies, and our maternal ability proxies. We add back the variation accounted for maternal unemployment exposure using the estimated coefficient. Lastly, we rescale the estimates of Panels (c) and (d) by adding the mean at zero unemployment computed in Panels (a) and (b). The local polynomial smoothing uses a bandwidth of 0.015. Bootstrapped standard errors are computed using 1,000 replications.

In Table 7, we also conduct a regression-based test for bunching to further validate our graphical results. This approach includes a dummy variable indicating zero unemployment exposure in the regression. If the coefficient on this dummy is not statistically significantly different from zero, it provides additional evidence against bias at the zero-unemployment threshold, further supporting the exogeneity assumption. Table 7 confirms that the dummy for zero unemployment is statistically indistinguishable from zero, supporting the conclusion that maternal unemployment is likely causing negative effects on children's outcomes. This result also holds for our sample without tail events, Columns 2, 3, and 4.

Table 7: Restricting Tail Events: Effects on Wages

	All Sample	UNEMP < p(95)	UNEMP < p(90)	UNEMP < p(85)
	(1)	(2)	(3)	(4)
	log(wage)	log(wage)	log(wage)	log(wage)
$1\{\text{UNEMP} = 0\}$	-0.005	-0.011	-0.013	-0.018
	(0.016)	(0.017)	(0.017)	(0.017)
OLF	-0.036	-0.028	-0.030	-0.028
	(0.026)	(0.026)	(0.027)	(0.027)
UNEMP	-0.220**	-0.394**	-0.376*	-0.636**
	(0.080)	(0.152)	(0.213)	(0.252)
Permanent Income	0.103**	0.103**	0.104**	0.103**
	(0.025)	(0.026)	(0.027)	(0.027)
Educ Dummies	Yes	Yes	Yes	Yes
Mom Educ Dummies	Yes	Yes	Yes	Yes
Mom AFQT	Yes	Yes	Yes	Yes
Remaining Unemp	Yes	Yes	Yes	Yes
F statistic	46.297	47.182	45.784	43.485
Observations	7,713	7,328	6,938	6,557
R2	0.273	0.268	0.265	0.268

Note: See Table 5 for the definition of variables and mothers' ability control. All models are estimated by two-stage least squares. Excluded instruments used in all Columns are the alternative permanent income measure and its interactions with dummy variables for mothers' marital and primary earner statuses. Standard errors are clustered at the children's level and reported in parentheses. The F statistic is the Kleibergen-Paap F statistic.
* and ** indicate statistically significant at the 10% and 5% levels.

4.6 Effects Across Labor Market Outcomes

We documented that maternal unemployment reduces children's labor market outcomes measured in adulthood and that these scaring effects extend beyond income loss and are not caused by endogeneity concerns. The scaring effects of maternal unemployment persist after controlling for proxies of mothers' ability and correcting for measurement error. They also pass placebo and bunching tests. However, most of our analysis only focuses on wages and employment probability. In this last subsection, we analyze other labor market outcomes: (1) total earnings, (2) wages, (3) weekly hours, and (4) employment probability. Table 8 presents the results of Table 5, Column 4 to these additional outcomes.

Column 1 shows that total earnings are negatively associated with non-participation exposure (significant) but exhibit no significant relationship with unemployment exposure. This lack of significance appears to result from opposing effects: Column 2 shows that wages decline with unemployment exposure (significant negative effect), while Column 3 shows that the workweek increases (significant positive effect). These effects offset each other, leading to a null impact on total earnings. Permanent income has a positive and significant effect on both total earnings and wages but does not significantly influence the workweek. Column 4 examines employment probability, finding no relationship between non-participation exposure and a significant negative association with unemployment exposure.

Table 8: All Labor Market Outcomes

	(1) log(total earn.)	(2) log(wage)	(3) log(hours)	(4) employed
OLF	-0.152**	-0.035	-0.031**	-0.132**
	(0.046)	(0.026)	(0.012)	(0.019)
UNEMP	-0.171	-0.213**	0.086**	-0.137*
	(0.150)	(0.078)	(0.037)	(0.070)
Permanent Income	0.086**	0.103**	-0.006	0.008
	(0.038)	(0.024)	(0.009)	(0.014)
Educ Dummies	Yes	Yes	Yes	Yes
Mom Educ Dummies	Yes	Yes	Yes	Yes
Mom AFQT	Yes	Yes	Yes	Yes
Add. unemp	Yes	Yes	Yes	Yes
F statistic	50.051	50.051	50.051	77.825
Observations	7,713	7,713	7,713	20,102
R2	0.232	0.273	0.069	0.094

Note: See Table 5 for the definition of variables and mothers' ability control. All models are estimated by two-stage least squares. Excluded instruments are the alternative permanent income measure and its interactions with dummy variables for mothers' marital and primary earner statuses. Standard errors are clustered at the children's level and reported in parentheses. The F statistic is the Kleibergen-Paap F statistic.
* and ** indicate statistically significant at the 10% and 5% levels.

4.7 Additional Robustness and Sensitivity Analyses

Other Forms of Selecting Matches In our analysis, we use the main match of the respondents, which we define as the job in which the respondents work the most hours at the time of the survey interview. We include multiple matches for the same respondent if he/she appears in multiple surveys. We tried four different sample selection methods to ensure the robustness of our findings: (1) selecting only the main match from the first survey where the respondent appears in our sample; (2) selecting only the main match from the last survey where the respondent appears in our sample; (3) including all jobs from all surveys where the respondent appears in our sample; and (4) averaging all jobs from all surveys where the respondent appears in our sample. In Table B1, we show that the results are robust regardless of how we select which match to include in our sample.

Non-Linear Effects on Wages and Employment Probabilities Table B2 examines the potential non-linear relationship between non-employment and children's wages and employment probability. It shows that the effects of maternal unemployment on wages do not exhibit strong non-linear patterns. In Subsection 4.4, we also report local regressions that support the linearity assumption.

Additional Information on Family Environment In Table B3, we add additional controls that capture various aspects of children's environment when growing up. Specifically, we include (i) a polynomial in the mother's age at childbirth, (ii) controls for spousal labor supply, (iii) measures of family structure and location, including the number of children in the household and whether the family lived in an urban or rural area, and (iv) the fraction of years the father and grandparents were present in the household. After accounting for these additional factors, the estimated impact of maternal unemployment on adult wages increases in magnitude and remains statistically significant.

Number of Unemployment Spells We decompose our exposure measure into the number of unemployment spells and the average exposure per unemployment spell. Table B4 shows the results. Overall, the number of maternal unemployment spells is negatively correlated with children's future wages, while the average duration is negatively correlated but not precisely estimated.

Fixed Effects The NLSY's panel structure allows us to examine the variation between siblings exposed to different quantities of maternal unemployment. In Table B5, we use mother-fixed effects and find that, in all specifications, the coefficients on unemployment exposure, non-participation exposure, and permanent income are statistically insignificant and have the opposite signs of the results without using fixed effects. We conjecture that there is little variation between siblings to account for after controlling for mother-fixed effects since siblings often share similar childhood conditions. For instance, two siblings with a two-year age gap share the same exposure to maternal unemployment for 16 years. The insignificant and negative coefficient on permanent income, while family income is positively related to offspring's human capital and labor market outcomes based on economic theory and other empirical results, suggests that the lack of variation between siblings is, indeed, a problem for the fixed-effect specification.

Effects by the Gender of the Child and Single Mom In Table B6, we test the heterogeneous effect of exposure to maternal unemployment and non-participation depending on the child's gender. We find that having the mother out of the labor force significantly reduces the employment probability of girls but has a very limited effect on boys. This might be explained by the transmission of gender roles from mothers to their daughters and is consistent with the findings of Galassi, Koll, and Mayr (2021). We find no gender heterogeneity in the effects on wages. B7 shows no substantial difference in the unemployment coefficient across single and married moms.

Birth and Prenatal Characteristics We also analyze birth and prenatal characteristics and their relationship to labor market outcomes. Specifically, we examine the child's birth order, gestation length (in weeks), birth weight (in ounces), and the shortest birth spacing in cases where the child has siblings. The last control is of particular interest in light of evidence from Dougan, García, and Polovnikov (2025), who show that the effectiveness of the Infant Health and Development Program (IHDP) depends on whether a child is a twin and, more broadly, on the spacing between births. Figure B8 shows no evidence that these controls affect our estimates of the impact of maternal unemployment.

Heterogeneous Effect: Measures of Mother's Ability In Figure C1, we test and conclude that maternal unemployment has no different effects depending on the mother's education and abilities.

Persistent Effect of Unemployment Over Age Groups We also check whether the effects of experiencing unemployment during childhood persist as individuals grow older. Figure C2 suggests that the negative effect remains over time.

Downstream Effect We control for a measure of permanent income to estimate the impact of unemployment not explained by the income channel. However, for that, it is crucial to estimate the coefficient on permanent income correctly. We deal with this concern first using instrumental variable estimation to correct for measurement error in permanent income. Additionally, in Figure C3, we use constrained regressions where the coefficient on permanent income is fixed at different values within a pre-specified grid.

For the estimated effect of unemployment to be fully accounted for by income (i.e., for the unemployment coefficient to reach zero), the true PI coefficient would need to be around 0.5. This value is five times larger than the OLS estimate and more than three times larger than the IV estimate. This suggests that income alone cannot fully explain the effects of unemployment unless one assumes an implausibly large coefficient on permanent income. In other words, unemployment likely has an independent impact beyond its effect through income. This highlights the importance of considering non-income channels when studying the consequences of unemployment.

Distinguishing Between Voluntary and Involuntary Unemployment Throughout most of the paper, we have examined two labor market statuses: unemployment and non-participation in the labor force. Unemployment is usually involuntary and caused by external factors beyond an individual's control; however, non-participation can be either voluntary or involuntary. In Table B9, we combine our unemployment and non-participation exposure measures into a single measure of non-employment exposure and instrument it with children's exposure to maternal employment in cyclical industries. The goal is to identify the effect of exposure to involuntary labor-market non-participation on children's outcomes. Mothers who work in more cyclical industries are more likely to experience involuntary job loss due to factors beyond their control. We interpret a mother's non-employment predicted by her industry's cyclical exposure as the involuntary portion of her non-employment. The specifications, in general, are not statistically significant potentially because of large standard errors driven by a weak-IV problem. However, the point estimate is in line with the results, which we interpret as maternal involuntary non-employment also having scarring effects on children's future labor market outcomes.

Local Labor Market and Mobility Table B15 Chetty et al. (2014b), Chetty et al. (2016), and Chetty, Dobbie, Goldman, Porter, and Yang (2024) document the importance of neighborhood environments in shaping children's long-term outcomes. To account for this channel, we use restricted-use County Geocode data to ensure that our findings are not simply driven by geographic location. While our data is limited to the county level–less granular than the neighborhood-level variation emphasized in prior work–it still allows a meaningful examination of the local environment. Table B.12 shows that county-level unemployment and income predict children's future wages. However, they are insufficient to account for the negative impact of maternal unemployment exposure, suggesting that the mechanisms at play go beyond local labor market conditions.

5 Mechanisms and Channels

We now look at other results to uncover the mechanisms behind the scarring effects of maternal unemployment. First, we show that these effects vary across the children's development stages. In particular, we show that they are concentrated in later childhood years.

Second, we use the ATUS and the CE to document how mothers invest in their children's human capital development. Mothers allocate most of the extra available time after unemployment to leisure. The time spent on activities related to children's human capital development doubles, even though the time increase is small in magnitude. Moreover, mothers reduce expenditure in categories related to children's human capital development during unemployment. The fact that unemployed mothers invest more time but cut expenditures in children's development implies that some input substitution occurs during unemployment.

Third, we look at other children's outcomes when still young children. In particular, using the different assessment tests available in the NLSY-CYA, we document that maternal unemployment does not seem to impact children's home environment and cognitive development.

Lastly, we look at other children's outcomes when adults. In particular, we look at the impact on educational attainment and occupational sorting. We document that children exposed to more maternal unemployment attain lower education levels and enter low-mean, low-variance occupations.

5.1 The Role of Timing: Exposure Across Childhood Stages

Our previous exercises documented the effect of total exposure to maternal non-employment during children's first 18 years. However, it could be that this effect varies across different stages of the child's development, especially since we know that the effect of family income varies across different development stages. For example, Caucutt and Lochner (2020) found stronger estimated effects of early income (relative to late income) on college attendance. They interpret their results through the lens of a structural model and conclude that early financial constraints are binding for some young parents. Also, based on other results, they further conclude that later financial constraints are also binding.

Therefore, our first step in uncovering the mechanisms behind the scarring effects of maternal unemployment is to examine how these effects vary across children's development stages. To do this, we estimate a modified version of equation 3, allowing the measure of exposure to maternal unemployment and non-participation to differ across development stages:

$$y_{it} = \alpha + \sum_j \beta_{1,j} UNEMP_{i,j} + \sum_j \beta_{2,j} OLF_{1,j} + \sum_j \beta_{3,j} PI_{i,j} + \gamma_1 X_i + \gamma_2 Z_{it} + \epsilon_{it} \ . \tag{4}$$

We use 3-year bins for the development stages to smooth the results, grouping them as 0–3, 3–6, 6–9, 9–12, 12–15, and 15–18. We also include 3 years before the child is born and three bins for years after the child is older than 18, 18–21, 21–24, and 24–27. We also construct permanent income measures for three broader periods: 0–6, 6–12, and 12–18. As before, we use instrumental variables to correct for measurement error.

Figure 3 shows that the impact of maternal unemployment is stronger when it occurs during late adolescence (ages 15–18). Early childhood exposure (ages 0–15) shows minimal long-term wage effects, with estimates centered around zero and wide confidence intervals. Post-18 exposure exhibits greater volatility, with some recovery but still negative estimates, particularly at ages 21–24. The results support the idea that exposure to maternal unemployment during key career formation years–such as adolescence–may disrupt choices regarding when and how to enter the labor market or key human capital accumulation decisions. Furthermore, the near-zero coefficients for pre-birth exposure and exposure after age 25 confirm the placebo tests, reinforcing that the observed effects are not driven by unobserved maternal characteristics alone.

Our findings are consistent with the finding that parental job displacement can influence children's labor market entry, potentially at the cost of lower long-term earnings. For example, Fradkin et al. (2019) find that children of displaced workers in Belgium tend to enter the labor market earlier. In the appendix, Figure C4 shows the results for non-participation exposure. Outside of a big negative outlier when children are between the ages of 12-15, non-participation exposure tends to be positively related to children's future wages.

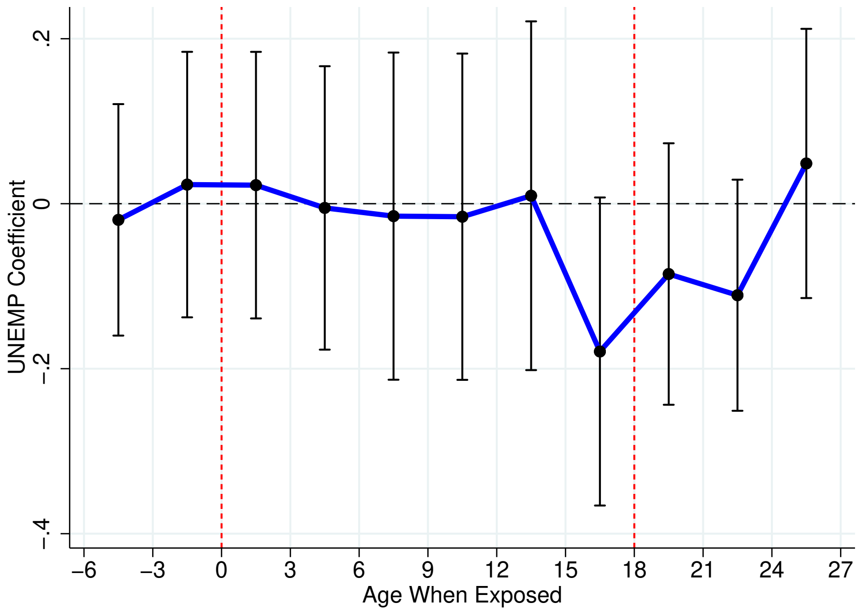


Figure 3: Impact of Maternal Unemployment on Wages by Childhood Stage

Note: This figure plots the estimated effect of maternal unemployment exposure on children's log wages at different age groups. The coefficients are obtained from an instrumental variables regression where log wages are regressed on unemployment exposure measures, three non-participation measures, three permanent income measures, child demographics (race, sex, age polynomials, education), maternal characteristics (marital status, primary earner status), and maternal quality proxies (AFQT, maternal education). We also create three permanent income instruments and interact them with maternal characteristics. The plot shows point estimates with 95% confidence intervals, adjusting for clustering at the individual level. The x-axis represents the child's age at the time of unemployment exposure, with negative values indicating exposure before birth. The vertical dashed line at age 0 marks birth, and the line at age 18 marks adulthood.

5.2 Early Childhood: Parental Time, Expenditure, and Human Capital Formation

Because we found no impact of early childhood exposure to maternal unemployment (ages 0–15) on children's long-term wages, we now examine potential mechanisms that could explain this result. In particular, we use the ATUS and CE to analyze how mothers invest in their children's human capital development. We find evidence of input substitution during unemployment, suggesting that mothers may decrease expenditures because of job loss but increase time to compensate for it. To investigate this mechanism further, we examine other child outcomes during early childhood. Specifically, we assess whether maternal unemployment affects the home environment and cognitive development. Our findings indicate no significant impact, which may explain why early-life exposure to maternal unemployment does not translate into lower wages for children.

Amount of Time Investment by Mothers' Labor Market Status

Unemployment decreases income but increases the time available to spend with children. Because we found no impact of early childhood exposure to maternal unemployment on children's long-term wages, a hypothesis is that the increased available time compensates for lower family income. Therefore, we use the Annual American Time Use Survey (ATUS) to investigate how mothers' time allocation varies given their labor market statuses. The ATUS measures how individuals divide their time among various activities. We look at the time allocation of women between 25 and 50 who reported having children under 18 living in the household. We provide a detailed description of the ATUS data and our sample in Appendix A.

In Table 9, we compare the time allocation of these women when they are employed, unemployed, and out of the labor force. For that, we compute the mean time spent on different activities and reweight the observations to correct for differences in the numbers of children across women with different employment statuses. The reweighting factor is the inverse of each employment status conditional probability on the number of children. We use four bins to discretize the number of children.

The most significant difference between employed and unemployed mothers is the substantially less time the latter spends on work and work-related activities. An employed mother works, on average, 6 hours and a half, while an unemployed mother works only half an hour. Unemployed mothers distribute this extra time in several other activities. They increase the time allocated to personal care and household activities by 137 minutes, to leisure by 105 minutes, and, crucially, to activities related to children's education by only 8 extra minutes. This increase seems small in magnitude, but it represents an increase of 77% relative to employed mothers. So, unemployed mothers almost double the time allocated to activities related to children's education.

Mothers out of the labor force spend more time with their children than those unemployed. We speculate that this can reflect self-selection into not working. Mothers who choose to be out of the labor force are likely to be more willing to spend time with their children and to invest their time in children's education and well-being. This can explain why the negative effects of mothers' non-participation are much lower than those of mothers being unemployed, which tends to be an involuntary state.

In Tables B12, B13, and B14, we do the reweighting to correct for other observable differences among labor market status groups. In particular, we correct for (i) differences in family income, (ii) differences in education levels, and (iii) differences in the age of the youngest child and the number of children. The time allocated to children's education is always higher for unemployed mothers than employed mothers, ranging from 70% to 80%. Therefore, it does not matter how we adjust for the differences in observables; unemployed mothers significantly increase their time investing in children.

Table 9: Average Number of Minutes per Mother' Status

	Emp	Unemp	OLF
Total Time Spent on All Activities	1440.00	1440.00	1440.00
Caring for and Helping Household Members	112.44	155.89	193.77
Caring for and Helping Children	90.83	132.75	169.39
Education-Related Activities for Children	10.74	19.00	21.10
Health-Related Activities for Children	3.17	4.77	4.79
Other Caring Activities for Children	76.92	108.97	143.50
Caring for and Helping Non-Household Members	6.40	14.47	11.92
Working and Work-Related Activities	384.05	35.84	5.25
Leisure and Social Activities	172.24	276.96	266.43
Purchasing Goods and Eating	103.09	125.69	130.45
Personal Care and Household Activities	634.48	771.85	778.23
Educational Activities	7.25	27.58	20.38
Other and Communication Activities	20.05	31.72	33.57

Note: The sample consists of women between 25 and 50 who reported having children under 18 living in the household. We look at the days of the week and non-holidays. We have 14,755 employed, 1,014 unemployed, and 5,135 out-of-the-labor-force respondents. Time allocation categories are the major BLS aggregate categories. Each cell represents averages. We use survey sample weights and construct additional weights to correct for differences in the number of children across employment status groups.

Amount of Money Investment by Mothers' Labor Market Status

Unemployed mothers almost double the time allocated to activities related to children's education, as shown in Table 9. Since they increase their home-based childcare, we now investigate whether these mothers spend less in categories associated with market-based investment in human capital. We use the Consumer Expenditure Survey (CE) to investigate the relationship between parental labor status and children-related expenditures. We provide a detailed description of the CE data and our sample in Appendix A.

The CE provides information on monthly household expenditures, family structure, and employment statuses of each household member. First, we aggregate expenditures into quarters. We also identify children-related expenditures based on the corresponding expenditure names in the CE. Examples are expenditures related to childcare, school and college tuition, apparel, and entertainment. Appendix A provides a complete description of these expenditure categories. Second, we record the employment status of both parents, where a parent can be either working or non-working. Non-working parents are further classified as unemployed and out of the labor force. A person is identified as unemployed if they (i) are not working and (ii-a) report inability to find a job as the reason for not working or (ii-b) have received unemployment benefits over the past 12 months. All other non-working parents are classified as out of the labor force.

We run OLS regressions where the dependent variables are a combination of all children-related expenditures. The main variables of interest are the labor market statuses of both parents. Controls include total expenditures, family size, the number of children younger than 16 years old, parental education, and time-fixed effects. Households with no children under the age of 16 are excluded from the sample.

Table 10, Column (1) shows that households with out-of-the-labor-force and unemployed mothers spend around 30% less on children-related expenditures relative to families with employed mothers. Similarly, households with out-of-the-labor-force and unemployed fathers also spend less on children-related expenditures, although the magnitude of the effect is weaker. Column (2) includes additional control for parental education, which reduces the negative effect of being non-employed. The estimated effects are stronger for out-of-the-labor-force parents than for unemployed parents, which could reflect unemployed parents spending time looking for jobs and not fully substituting market-based inputs or unobservable differences between out-of-the-labor-force and unemployed parents.

Columns (3) and (4) look at the share of expenditures dedicated specifically to childcare among households with children under the age of two. Share of childcare expenditures is, on average, 6-7 pt lower in households with non-working mothers relative to families where mothers are employed. The effect for out-of-the-labor-force mothers is stronger, consistent with the results in Columns (1) and (2). Moreover, the effect of paternal employment status is much weaker, indicating that fathers do not tend to substitute market-based childcare services. Importantly, these results are consistent with our evidence on the time of use, showing that there is a substitution of home-based and market-based inputs depending on the labor market statuses of the mothers.

The Impact on Home Environment and School Performance

We further investigate our finding that exposure to maternal unemployment appears to have little impact when experienced in early childhood. In particular, we use two assessment tests available in

Table 10: Child-related expenditures (CE)

	(1) log kids exp	(2) log kids exp	(3) childcare share	(4) childcare share
Mother OLF	-0.339**	-0.314**	-0.075**	-0.072**
	(0.012)	(0.011)	(0.003)	(0.003)
Mother Unemployed	-0.282**	-0.246**	-0.060**	-0.056**
	(0.056)	(0.056)	(0.013)	(0.012)
Father OLF	-0.166**	-0.148**	-0.014**	-0.015**
	(0.025)	(0.024)	(0.007)	(0.007)
Father Unemployed	-0.192**	-0.171**	-0.036**	-0.029**
	(0.063)	(0.062)	(0.015)	(0.015)
Constant	-0.658**	0.001	0.087**	0.175**
	(0.068)	(0.174)	(0.017)	(0.038)
Number of children	Yes	Yes	Yes	Yes
Family size	Yes	Yes	Yes	Yes
Total expenditures	Yes	Yes	Yes	Yes
Time fixed effects	Yes	Yes	Yes	Yes
Parental education		Yes		Yes
Observations	61,424	61,424	13,636	13,636
R2	0.220	0.233	0.093	0.111
Engel curve			1.100	0.929

Note: Mother OLF/Unemployed and Father OLF/Unemployed represent dummy variables corresponding to labor statuses of each parent. Base categories are working mother and working father. Baseline controls include number of children younger than 16 years old, number of household members, total expenditures, year and quarter fixed effects. Columns (2) and (4) additionally account for parental education defined as the maximum of the maternal and paternal educational levels. Sample size in Columns (3) and (4) is smaller, since it includes only families with children under the age of 2. All models are estimated by ordinary least squares. Standard errors are reported in parentheses.
* and ** indicate statistically significant at the 10% and 5% levels.

the NLSY-CYA to document how maternal unemployment impacts children's development. First, we use the HOME (Home Observation for Measurement of the Environment) Inventory, which measures the quality of the child's home environment. Second, we use the Peabody Individual Achievement Test (PIAT), which measures children's cognitive achievements.

In Table 11, we investigate these relations by projecting the standardized test scores on maternal unemployment exposure, maternal labor-market non-participation exposure, and family permanent income. Test scores are measured when children are between 7 and 9 years old, while the other variables are measured when they are between 0 and 5 years old. We include maternal education attainment and AFQT quintile dummies to capture mothers' latent abilities and childcare skills, dummy variables for children's race and gender, a cubic polynomial in children's age, and survey-year fixed effect. We also correct for measurement error.

In Column 1, we document a negative but statistically insignificant relationship between exposure to maternal unemployment and the overall home environment. In Column 2, we find a negative relationship between maternal unemployment exposure and emotional support, though this estimate is not statistically significant. In Column 3, the relationship between maternal unemployment and cognitive stimulation is small and also statistically insignificant. In Columns 4 and 5, we document positive but statistically insignificant relationships between maternal unemployment exposure and both the average PIAT and Math PIAT scores. In sum, the results indicate that maternal unemployment does not have a statistically significant impact on the home environment or cognitive development measures.

Table 11: The Impact on Home Environment and Overall Development

	(1) HOME Total	(2) Emotional	(3) Cognitive	(4) Avg. PIAT	(5) Math PIAT
OLF 0-5	-0.054	-0.042	-0.028	0.000	-0.036
	(0.062)	(0.071)	(0.068)	(0.069)	(0.067)
UNEMP 0-5	-0.256	-0.327	-0.021	0.034	0.180
	(0.211)	(0.217)	(0.236)	(0.209)	(0.217)
Permanent Income 0-5	0.220**	0.079	0.274**	0.176**	0.090
	(0.056)	(0.060)	(0.060)	(0.067)	(0.063)
Mom Educ Dummies	Yes	Yes	Yes	Yes	Yes
Mom AFQT	Yes	Yes	Yes	Yes	Yes
F statistic	36.693	36.914	35.709	40.474	40.474
Observations	5,845	5,577	5,712	5,640	5,640
R2	0.340	0.262	0.253	0.172	0.169

Note: OLF and UNEMP are our exposure measures to maternal labor-force non-participation and unemployment, respectively. See equation (1) for construction details. Permanent Income is in $10,000s (discounted present value) as of birth year. See equation (2) for construction details. OLF, UNEMP, and PI are measured when children are between 0 and 5 years old. Controls include maternal education attainment and AFQT quintile dummies, dummy variables for children's race and gender, a cubic polynomial in children's age, and survey-year-fixed effect. Dependent variables are total HOME score, emotional support HOME score, cognitive stimulation HOME score, average PIAT score, and PIAT MATH score. All are measured when children are between 7 and 9 years old. The average PIAT score is an average of the PIAT Math, PIAT Reading Recognition, and Reading Comprehension. Standard errors are clustered at the children's level and reported in parentheses. The F statistic is the Kleibergen-Paap F statistic.
* and ** indicate statistically significant at the 10% and 5% levels.

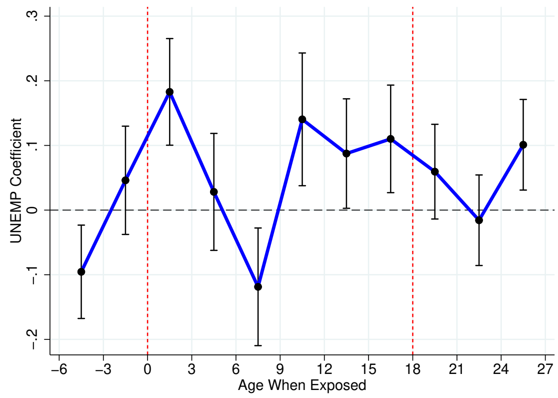
5.3 Late Childhood: Education and Occupational Sorting

We found that the impact of maternal unemployment is significant when experienced during late adolescence (ages 15–18). We now examine potential mechanisms that could explain this result. In particular, we will test the hypothesis that exposure to maternal unemployment during key career formation years–such as adolescence–may disrupt choices regarding when and how to enter the labor market or key human capital accumulation decisions.

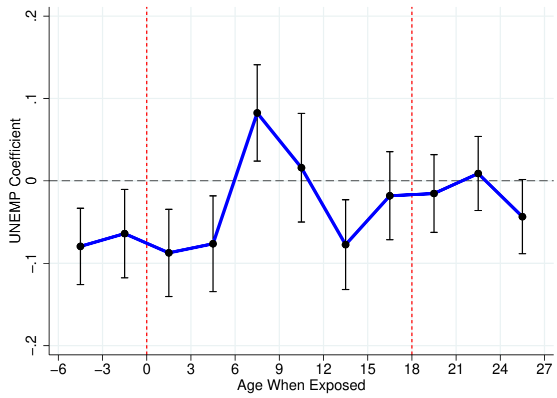
Figure 4 has four panels. Each panel represents a different outcome that we project in maternal unemployment exposure bins by estimating equation (4). Panel (a) and (b) plot the life cycle pattern of the effect of maternal unemployment on the probability of a child dropping out of high school or completing college or more. Ages 15–18 are critical for high school completion and college decisions. However, unemployment exposure is harmful at all childhood stages and not uniquely at ages 15–18. Moreover, there is an outlier at ages 6 and 9 that we cannot account for.

Figure 4, Panels (c) and (d) plot the life cycle pattern of the effect of mean return and risk of the occupation that children report having when adults. We use CPS data and estimate Mincer equations to construct this index. The mean return is the coefficient on occupation dummies obtained after regressing the logarithm of wages on controls and these occupation dummies. This captures the average wage premium associated with each occupation after accounting for key demographic characteristics. The risk measure is constructed by first estimating wage residuals from the regression, squaring them, and then averaging these squared residuals within each occupation. This risk measure captures the within-occupation wage variability, reflecting potentially the risk in earnings that workers in each occupation may experience. Panels (c) and (d) show that maternal unemployment exposure predicts that children will work in low-mean, low-variance occupations. In particular, the result is marked for ages 15–18.

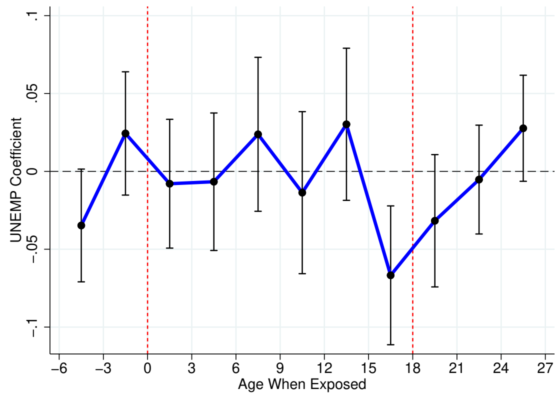
Figure 4: Education and Occupational Sorting



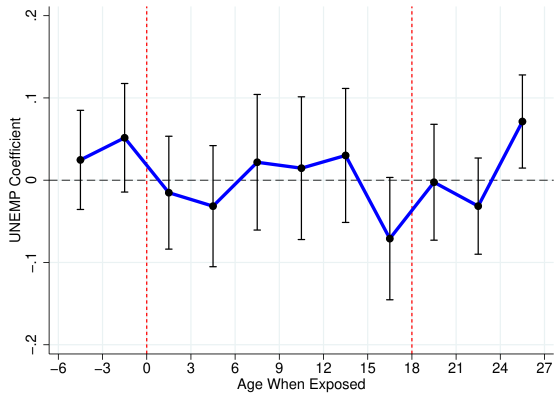
(a) Probability of Being Dropout



(b) Probability of Attending College



(c) Outcome



(d) Placebo Outcome

In terms of utility, a child is worse off with a lower mean but better with a lower risk. We can compute how much worse it is by assuming a utility function and some parameters. In particular, we assume a CRRA utility that is a function of wages and has a coefficient of risk aversion of 2. Furthermore, we assume that wages are log-normally distributed. The expected utility is $-e^{-\mu+\frac{1}{2}\sigma^2}$. In our exercise, the average mean and variance are normalized to one; therefore, the reference child has an expected utility of -0.6065. The child exposed to one standard deviation more maternal unemployment has an expected utility of -0.6063. Our results show that, even though a more exposed child chose different occupations, in terms of utility, this difference is small. (Actually, in our simple example, the exposed child is better off.)[7]

6 Conclusion

In this paper, we revisit whether exposure to maternal non-employment affects children's future labor market outcomes. We use an approach that allows us to isolate the income effect and to account for different unemployment patterns. In particular, we construct a measure of children's exposure to maternal unemployment using NLSY79 and NLSY79-CYA. We show that the amount of time a mother spends unemployed when her child is growing up is negatively associated with the child's employment probability and future wage. Moreover, we document that this negative relation is present even when controlling for family permanent income, suggesting that the negative effect of unemployment goes beyond the decrease in income and that mothers' extra time at home does not mitigate it.

We further show evidence that our results are likely not driven by measurement error or unobservable mother characteristics. On the contrary, our results suggest that mothers' inability to find a job directly affects children's labor market outcomes. We investigate potential mechanisms by looking at how the impact of unemployment changes when experienced over different childhood stages. We document that the impact is concentrated in late adolescence, potentially related to decisions about when these children enter the labor market.

[7]The utility is $U(w) = \frac{w^{1-\gamma}}{1-\gamma}$ or $U(w) = -\frac{1}{w}$ after assuming $\gamma = 2$. Under log-normality, $E(U(w)) = -E(\frac{1}{w}) = -E(e^{-\ln(w)}) = -e^{-\mu+\frac{1}{2}\sigma^2}$.

The mean return and risk slope coefficients are -0.0667529 and -0.0709941 for the unemployment exposure when aged between 15 and 18. The standard deviation of unemployment exposure is 0.10 also for those ages. Plugging these numbers into the formula, we obtain our result.

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A Data

A.1 NLSY Data Details

Our primary datasets are the National Longitudinal Survey of Youth 1979 (NLSY79) and the NLSY79 Child and Young Adult (NLSY79-CYA). The NLSY79 is a nationally representative sample of over 12,000 individuals aged 14-22 in 1979, providing a comprehensive longitudinal study of their lives and labor market experiences. The NLSY79-CYA contains information on children born to women in the original NLSY79 cohort, spanning from 1980 to 2018. The BLS has identified 11,551 children as having been born to the original 6,283 NLSY79 female respondents (as of 2018).

Table A1: Summary Statistics by Employment and Wage Availability

	Non-missing Emp Status	Non-missing Wage
Sample size	22,920	8,681
Unemployment Exposure	0.052	0.047
	(0.074)	(0.070)
Non-participation Exposure	0.355	0.332
	(0.295)	(0.281)
Permanent Income	0.798	0.857
	(0.810)	(0.848)
Age	28.30	28.10
	(4.63)	(4.27)
Log Wage	2.23	2.25
	(0.44)	(0.42)
Log Hours	3.72	3.72
	(0.20)	(0.19)

The Young Adult sample within the NLSY79-CYA is what enables us to study the long-term labor market impacts of maternal unemployment on children. The Young Adult sample refers to a questionnaire that has been administered to children aged 15 and older since 1994. The questionnaire was designed to facilitate life-cycle and cross-generational analyses. Of all identified children, 4,354 were interviewed as young adults. Details on the sizes and eligibility criteria vary by year. Those interested should look for details in the NLSY documentation.

Table A.1 has the descriptive statistics of our final samples. We include only young adults who have reached working age in our analysis. Column 1 shows the statistics for the respondents with non-missing values for employment status, child's gender, child's race, and child's age. Overall we have 22920 person-year non-missing employment observations. Column 2 shows the statistics for those who have non-missing values for wage, hours worked, total income, and child's gender, child's race, and child's age. There are 8682 person-year non0missing wage observations. The continuous variables display the mean and the standard deviation in parenthesis, while the categorical variables are described as fractions corresponding to each level.

UNEMP and OLF correspond to the exposures to maternal unemployment and non-participation in the labor force and are defined as in 1, taking values from 0 to 1. Permanent income is defined in 2 and is expressed in 10000s of 1993 US dollars. Age corresponds to the young adult's age at the time of the survey. Log wage refers to a logarithm of hourly wages, while log hours – to a logarithm of weekly hours. Education and Mother's Education indicate the highest attained education level for the young adults and their mothers respectively.

Notice, that Column 1 includes non-employed young adults, while Column 2 does not. This might explain why education levels are lower in Column 1. The rest of the variables have similar distributions across the two samples.

A.2 CES Data Details

The Current Employment Statistics (CES) data is a monthly survey conducted by the Bureau of Labor Statistics (BLS). It provides detailed information on employment, hours, and earnings of workers on nonfarm payrolls. Our exercise uses employment estimates for total nonfarm employment and by industry sector.

We use three-digit industries, but to describe the data in this appendix, we divide employment into 15 industries, as seen in Table A2. We use data spanning January 1972 to December 2019. Because, during these years, the US experienced significant changes in its sectorial composition, we show the total number of employees in each industry and their share of total employment in December 1972 and December 2019. The industries that gained employment share were financial activities, professional and business services, and private education and health services. Those that lost were construction, durable goods, and other services. We deliberately exclude the COVID-19 pandemic years from the sample.

We estimate the cyclical sensitivities of industries following the method of McLaughlin and Bils (2001). To account for the trend in sectorial composition, we use a cubic trend, which is flexible enough to capture it in these sectors. In the text, we mentioned that we estimate equation (5) in first-difference, but we actually use quarter changes, i.e., $E_{it} - E_{it-3}$. The reason is that we are interested in business cycle fluctuations, and we believe that monthly changes are too high-frequency. Ultimately, there is not much difference in the cyclical sensitivity β_i^e when using monthly or quarterly changes. Our estimated β_i^e's are displayed in Column 6.

A.3 ATUS Data Details

The American Time Use Survey (ATUS) is an annual survey conducted by the Bureau of Labor Statistics (BLS) to measure how the American population spends their time on different activities such as paid work, childcare, volunteering, and socializing. Participants are interviewed once and asked to describe their previous day's activities, which are then categorized.

The ATUS sample is derived from households that have conducted their eighth interview for the Current

Table A2: Cyclical Sensitivities

	dez/1972		dez/2019		
	Empl. (1,000)	Share	Empl. (1,000)	Share	β_i^e
All industries	**75,268**	**100.0%**	**151,666**	**100.0%**	
Mining and logging	677	0.9%	708	0.5%	0.05
Construction	3,937	5.2%	7,541	5.0%	2.09
Durable goods	11,036	14.7%	8,022	5.3%	1.35
Nondurable goods	7,122	9.5%	4,794	3.2%	-0.06
Wholesale trade	3,578	4.8%	5,895	3.9%	0.14
Retail trade	8,227	10.9%	15,509	10.2%	-0.05
Transportation and warehousing	2,678	3.6%	5,736	3.8%	0.43
Utilities	564	0.7%	548	0.4%	-0.95
Information	2,096	2.8%	2,885	1.9%	0.24
Financial activities	3,842	5.1%	8,814	5.8%	-0.29
Professional and business services	5,668	7.5%	21,443	14.1%	0.21
Private education and health services	4,975	6.6%	24,391	16.1%	-0.77
Leisure and hospitality	5,240	7.0%	16,761	11.1%	-0.17
Other services	1,944	2.6%	5,911	3.9%	-0.49
Government	13,684	18.2%	22,709	15.0%	-0.85

Note: See text for details.

Population Survey (CPS). The ATUS survey selects roughly 25% of these households randomly to participate in the time-use survey. One individual aged 15 or above is chosen from each household to participate in the survey. Key demographic data collected in the CPS is transferred to the ATUS. This includes household membership, employment status, earnings, and other characteristics. We use data spanning 2003 and 2021 and focus on women between 25 and 50 who reported having children under 18 living in the household.

A.4 CE Data Details

Consumer Expenditure Surveys (CE) are conducted by the Census Bureau for BLS. For our analysis we use Interview Surveys of CE for 2000-2020, which collect information on monthly household expenditures, incomes, and household characteristics. Households are surveyed for five consecutive quarters and are then dropped from the sample. The survey collects detailed data on each household member, including income, employment status, education, gender, and relation to the respondent. We use this information to determine parental employment statuses and education levels.

The expenditures are recorded using Universal Classification Codes (UCC) and cover a wide range of personal consumption categories. We identify children-related expenditures based on whether the name of the expenditure contains one of the following children-related keywords: "infant", "nursery", "baby", "child", "boy", "girl", "school", "toys", "playground", "college", "tutoring". We then classify expenditures associated with babysitting, childcare, and daycare (UCC codes: 340210-340212, 670310) as childcare-related.

B Additional Tables

B.1 Other Matches

In our analysis, we use the main match of the respondents, which we define as the job in which the respondents work the most hours at the time of the survey interview. This implies that, in our sample, respondents may appear several times if they participated in more than one survey wave when adults. As robustness, we try four different rules of selecting the match: (1) we select the first match in which the respondent appears in our sample, which implies that he will appear only once in the sample; (2) we select the last match in which the respondent appears in our sample, which also implies that he will appear only once; (3) we include all matches not only the main match, which implies that the respondent might appear several times even within the same survey year; and (4) averaging all jobs from all surveys where the respondent appears in our sample.

In Table B1, we estimate equation (3) controlling only for permanent income and show that there is no impact by the way we select the sample. Exposure to maternal unemployment and labor market non-participation has almost the same effect regardless of how we select which match to include in our sample.

Table B1: Other Matches

	Main Match	First Match	Last Match	All Matches	Avg. of Matches
	(1)	(2)	(3)	(4)	(5)
	log(wage)	log(wage)	log(wage)	log(wage)	log(wage)
OLF	-0.121**	-0.099**	-0.095**	-0.114**	-0.097**
	(0.024)	(0.024)	(0.025)	(0.023)	(0.021)
UNEMP	-0.377**	-0.446**	-0.437**	-0.345**	-0.487**
	(0.076)	(0.079)	(0.085)	(0.074)	(0.076)
Permanent Income	0.105**	0.094**	0.111**	0.099**	0.108**
	(0.010)	(0.009)	(0.010)	(0.009)	(0.009)
Observations	8,376	4,116	4,116	10,943	4,269
R2	0.193	0.187	0.188	0.198	0.183

Note: Columns differ in their sample. See text for details. OLF and UNEMP are our exposure measures to maternal labor-force non-participation and unemployment, respectively. See equation (1) for construction details. Permanent Income is in $10,000s (discounted present value) as of birth year. See equation (2) for construction details. Controls include dummy variables for children's race and gender, a cubic polynomial in children's age, and fixed effects for the survey year. All columns are estimated by ordinary least squares. Standard errors are clustered at the children's level and reported in parentheses.
* and ** indicate statistically significant at the 10% and 5% levels.

B.2 Non-Linear Effects on Wages and Employment Probabilities

Table B2 explores the non-linearity of the relationship between maternal non-employment and children's labor market outcomes. In particular, we split exposures to unemployment and to maternal labor-force non-participation into 4 groups and re-estimate the equation 3. The bins are grouped differently since the exposure to labor-force non-participation is much more dispersed and has a much higher mean than unemployment. For the unemployment exposure, percentiles 25, 50, and 75 are approximately 14 days, 5 months, and 1 year and 3 months. For the non-participation exposure, percentiles 25, 50, and 75 are approximately 1 year and 9 months, 5 years and 3 months, and 9 years and 10 months.

After controlling for instrumented permanent income, we find that maternal labor-force non-participation does not have any significant effect on children's wages when the mother is out of the labor force for less than 9 years. The effects of maternal unemployment on children's wages are more linear. The effects on the child's employment outcome are slightly different. In this case, exposure to unemployment for less than a year does not seem to affect children's employment probability. In Subsection 4.4, we also report local regressions that support the linearity assumption.

Table B2: Exploring Non-linearity in the Effects of Maternal Labor-Force Non-Participation

	OLS	IV	OLS	IV
	(1)	(2)	(3)	(4)
	log(wage)	log(wage)	emp.	emp.
OLF p25-50	-0.017	0.018	-0.015	-0.007
	(0.017)	(0.018)	(0.012)	(0.012)
OLF p50-75	-0.042**	0.002	-0.074**	-0.064**
	(0.017)	(0.018)	(0.012)	(0.013)
OLF p75-100	-0.113**	-0.046**	-0.149**	-0.109**
	(0.018)	(0.020)	(0.012)	(0.014)
UNEMP p25-50	-0.040**	-0.007	-0.019	-0.016
	(0.017)	(0.017)	(0.012)	(0.012)
UNEMP p50-75	-0.105**	-0.061**	-0.006	-0.005
	(0.018)	(0.018)	(0.013)	(0.013)
UNEMP p75-100	-0.137**	-0.072**	-0.063**	-0.050**
	(0.019)	(0.019)	(0.013)	(0.014)
Permanent Income		0.157**		0.037**
		(0.022)		(0.013)
F statistic		58.428		105.206
Observations	9,203	9,203	22,920	21,737
R2	0.184	0.209	0.063	0.065

Note: OLF and UNEMP are our exposure measures to maternal labor-force non-participation and unemployment, respectively. See equation (1) for construction details. Permanent Income is in $10,000s (discounted present value) as of birth year. See equation (2) for construction details. Controls in Columns (1) and (3) include dummy variables for children's race, gender, and educational attainment, a cubic polynomial in children's age, and fixed effects for the survey year. Columns (2) and (4) also include dummy variables for mothers' marital and primary earner statuses. Columns (1) and (3) are estimated by ordinary least squares, while Columns (2) and (4) by two-stage least squares. Excluded instruments are the alternative permanent income measure and its interactions with dummy variables for mothers' marital and primary earner statuses. Standard errors are clustered at the children's level and reported in parentheses.
* and ** indicate statistically significant at the 10% and 5% levels.

B.3 Additional Controls

In our main analysis, we control for many variables, particularly our three proxies for mothers' abilities. We add additional controls that capture other aspects of children's environment when growing up in Table B3. Column 1 replicates the baseline result from Table 5, Column 4. Column 2 controls for a polynomial in the mother's age at childbirth. Column 3 adds the spouse's average weekly hours and weeks worked to capture the impact of spousal labor supply. Column 4 includes the average number of children in the household and whether the family lived in an urban or rural area, capturing family structure and location. Column 5 includes the fraction of years that the grandparents and the father were present in the household. Column 6 includes all of these additional controls simultaneously. Notably, after controlling for all these additional aspects of children's environment, the estimated impact of maternal unemployment on adult wages increases from -0.21 to -0.32, remaining highly significant. In contrast, the coefficient on maternal non-participation in the labor force remains statistically insignificant across specifications.

Table B3: Robustness: Additional Controls

	Baseline	w/ Mom's Age	Mom's Spouse	Family Envir.	HH Composition	All Controls
	(1)	(2)	(3)	(4)	(5)	(6)
	log(wage)	log(wage)	log(wage)	log(wage)	log(wage)	log(wage)
OLF	-0.035	-0.033	-0.026	-0.037	-0.034	-0.025
	(0.026)	(0.026)	(0.028)	(0.026)	(0.026)	(0.028)
UNEMP	-0.214**	-0.214**	-0.324**	-0.214**	-0.212**	-0.323**
	(0.078)	(0.078)	(0.088)	(0.078)	(0.078)	(0.087)
Permanent Income	0.102**	0.101**	0.108**	0.102**	0.103**	0.104**
	(0.024)	(0.025)	(0.025)	(0.026)	(0.024)	(0.027)
Educ Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Mom Educ Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Mom AFQT	Yes	Yes	Yes	Yes	Yes	Yes
Add. unemp	Yes	Yes	Yes	Yes	Yes	Yes
Mom Cubic in Age		Yes				Yes
Mom' Spouse Labor Supply			Yes			Yes
Family Environment				Yes		Yes
Household Composition					Yes	Yes
F statistic	49.962	49.199	48.614	44.030	49.383	40.467
Observations	7,707	7,707	6,905	7,695	7,707	6,893
R2	0.273	0.274	0.268	0.276	0.273	0.272

Note: See Tables 5 for the definition of mothers' ability control and for the construction of other variables. See text for additional controls. All models are estimated by two-stage least squares. Excluded instruments are the alternative permanent income measure and its interactions with dummy variables for mothers' marital and primary earner statuses. Standard errors are clustered at the children's level and reported in parentheses. The F statistic is the Kleibergen-Paap F statistic.

* and ** indicate statistically significant at the 10% and 5% levels.

B.4 Number of Unemployment Spells

Our main analysis focuses on the total exposure to maternal unemployment. It is possible to decompose our measure to the number of unemployment spells and the average exposure per unemployment spells. To implement this specification, we count the number of times that a respondent transitioned from any labor market status to unemployment. Then, we create the average exposure by dividing our original measure by the number of unemployment spells. We define the average unemployment exposure as zero when the mother experienced no unemployment spells.

Table B4 shows the results. In Column 1, we observe that a greater number of maternal unemployment spells is significantly associated with lower wages, with a coefficient of -0.007, significant at the 5% level. The number of out-of-labor-force spells appears to have no significant impact on wages. In Column 2, the estimated coefficient on average unemployment exposure is negative (-0.359) but is not statistically significant due to the high standard error. Similarly, the coefficient on average OLF exposure is negative but imprecisely estimated. Lastly, in Column 3, we includes both measures simultaneously. The coefficient on the number of unemployment spells remains negative and statistically significant, while the coefficient on average unemployment exposure remains negative but imprecisely estimated. This suggests that frequency rather than duration per spell may be the more important mechanism.

Table B4: Robustness: Number of Unemployment Spells

	(1) log(wage)	(2) log(wage)	(3) log(wage)
Number of OLF Spells	0.001		0.000
	(0.002)		(0.002)
Average OLF		-0.020	-0.061
		(0.050)	(0.053)
Number of UNEMP Spells	-0.007**		-0.007**
	(0.003)		(0.003)
Average UNEMP		-0.359	-0.254
		(0.305)	(0.301)
Permanent Income	0.112**	0.117**	0.103**
	(0.024)	(0.023)	(0.024)
Educ Dummies	Yes	Yes	Yes
Mom Educ Dummies	Yes	Yes	Yes
Mom AFQT	Yes	Yes	Yes
Remaining Unemp	Yes	Yes	Yes
F statistic	66.670	77.717	61.233
Observations	7,672	7,672	7,672
R2	0.273	0.270	0.274

Note: See Tables 5 for the definition of mothers' ability control and for the construction of other variables. See text for additional controls. All models are estimated by two-stage least squares. Excluded instruments are the alternative permanent income measure and its interactions with dummy variables for mothers' marital and primary earner statuses. Standard errors are clustered at the children's level and reported in parentheses. The F statistic is the Kleibergen-Paap F statistic.
* and ** indicate statistically significant at the 10% and 5% levels.

B.5 Fixed-Effect Results

In our analyses, we explore the variation between children in the sample. The panel structure of the NLSY allows us to explore variation within families. Specifically, we can examine the variation between siblings who were exposed to different quantities of maternal unemployment. To explore this variation, we estimate equation (3) using the mother-fixed effects.

Table B5, Columns 1 and 2 present the OLS results, and Columns 3 and 4 show the IV results, all allowing for mother-fixed effects. An interesting finding across all columns is that none of the coefficients on unemployment and non-participation exposure measures or the permanent income measure are statistically significant. Notably, the signs of the coefficients are opposite to the results without using fixed effects. A possible explanation for this result is that siblings often share similar childhood conditions. For instance, two siblings with a two-year age gap share the same exposure to maternal unemployment for 16 years. Consequently, there is little variation between siblings to account for after controlling for mother-fixed effects. Moreover, the insignificant and negative coefficient on permanent income, while family income is positively related to offspring's human capital and labor market outcomes based on economic theory and other empirical results, suggests that the lack of variation between siblings is, indeed, a problem in this fixed-effect specification. Table B5 shows that the employment probability results follow a similar pattern.

Table B5: Fixed-Effect Results: Wages

	OLS		IV	
	(1)	(2)	(3)	(4)
	log(wage)	log(wage)	log(wage)	log(wage)
OLF	0.055	0.045	0.023	-0.035
	(0.094)	(0.094)	(0.072)	(0.050)
UNEMP	0.260	0.297	0.340	-0.099
	(0.285)	(0.293)	(0.238)	(0.140)
Permanent Income	-0.029	-0.016	0.160	0.185**
	(0.046)	(0.047)	(0.136)	(0.077)
Educ Dummies		Yes	Yes	Yes
Mom Controls		Yes	Yes	Yes
F statistic			54.327	229.878
Observations	8,680	8,287	7,350	20,565
R2	0.678	0.691	0.156	0.022

Note: Column 1 includes dummy variables for children's race, a cubic polynomial in children's age, and fixed effects for the survey year. Column 4 includes, in addition, dummy variables for educational attainment, mothers' marital status, and primary earner status. These equations were estimated by ordinary least squares. Columns 4 and 5 include dummy variables for children's race, a cubic polynomial in children's age, fixed effects for the survey year, children's educational attainment dummies, and mothers' marital and primary earner status dummies. These equations were estimated by two-stage least squares. Excluded instruments used in all columns are the alternative permanent income measure and its interactions with dummy variables for mothers' marital and primary earner statuses. All columns include mother-fixed effects. Standard errors are reported in parentheses. They are clustered at the children's level for Columns 1 to 3 but not for Columns 4 and 5. Clustering made the estimated covariance matrix not of full rank. The F statistic is the Cragg-Donald Wald F statistic, which assumes that the errors are independent and identically distributed. This might not be true in our context, and the results should be interpreted with caution.
* and ** indicate statistically significant at the 10% and 5% levels.

B.6 Effects by the Gender of the Child

In our main analysis, we assume that the effects of exposure to maternal non-employment are homogeneous across children of different genders. However, this might not be the case since there are significant gender labor supply differences. To test whether the effects of maternal non-employment depend on the gender of the child, we re-estimate equation 3 by including interactions between the gender of the kid and the exposure to maternal non-employment (both OLF and UNEMP).

Table B6 shows the results. Columns 1 and 3 replicate the results from the baseline regressions, and Columns 2 and 4 include the interaction terms. Column 2 shows no gender heterogeneity in the effects of maternal non-employment on children's future wages. However, the effects of maternal non-employment on children's employment probability are different depending on the gender of the child. For example, exposure to an out-of-the-labor-force mother significantly reduces employment probability for daughters but not sons. This can be a result of gender norm transmission within the family. Daughters who grow up with non-working mothers are more likely to choose not to work. On the other hand, maternal unemployment reduces employment probability for sons but not for daughters. This might be because sons are more likely to be negatively affected by a stressful home environment.

Table B6: Differences by Gender

	(1) log(wage)	(2) log(wage)	(3) emp.	(4) emp.
OLF	-0.035	-0.043	-0.132**	-0.057**
	(0.026)	(0.034)	(0.019)	(0.024)
UNEMP	-0.214**	-0.210*	-0.137*	-0.293**
	(0.078)	(0.111)	(0.070)	(0.096)
Permanent Income	0.102**	0.103**	0.008	0.008
	(0.024)	(0.024)	(0.014)	(0.014)
Female	-0.103**	-0.108**	-0.054**	-0.018
	(0.012)	(0.019)	(0.009)	(0.014)
Female # OLF		0.017		-0.152**
		(0.043)		(0.032)
Female # UNEMP		-0.006		0.291**
		(0.136)		(0.121)
Educ Dummies	Yes	Yes	Yes	Yes
Mom Educ Dummies	Yes	Yes	Yes	Yes
Mom AFQT	Yes	Yes	Yes	Yes
Add. unemp	Yes	Yes	Yes	Yes
F statistic	49.962	50.161	77.825	78.168
Observations	7,707	7,707	20,102	20,102
R2	0.273	0.273	0.094	0.097

Note: See Tables 5 for the definition of mothers' ability control and for the construction of other variables. Controls include dummy variables for children's race, and educational attainment, a cubic polynomial in children's age, and fixed effects for the survey year, mothers' marital and primary earner statuses. All columns are estimated by two-stage least squares. Excluded instruments are the alternative permanent income measure and its interactions with dummy variables for mothers' marital and primary earner statuses. Standard errors are clustered at the children's level and reported in parentheses.

* and ** indicate statistically significant at the 10% and 5% levels.

B.7 Effects by the Single Mom

We use household composition variables to measure the presence of a spouse in the household over time. Specifically, we count the number of survey waves in which the respondent's spouse was present and divide the sample into two groups: (i) respondents with spousal presence frequency below the median and (ii) respondents with spousal presence frequency above the median. We then estimate separate regressions for each group. Table B7 shows no substantial difference in the unemployment coefficient across groups, suggesting that having a spouse present does not significantly alter the long-term effects of maternal unemployment on wages.

Table B7: Differences by Single Mom

	No Spouse Present	Spouse Prent
	(1)	(2)
	log(wage)	log(wage)
OLF	-0.159**	-0.111**
	(0.031)	(0.016)
UNEMP	-0.142*	-0.327**
	(0.084)	(0.076)
Permanent Income	0.030	0.003
	(0.027)	(0.011)
Educ Dummies	Yes	Yes
F statistic	163.124	.
Observations	11,019	9,529
R2	0.087	0.076

Note: See Tables 5 for the definition of mothers' ability control and for the construction of other variables. Controls include dummy variables for children's race and educational attainment, a cubic polynomial in children's age, fixed effects for the survey year, and dummies for primary earner status. We do not include marital status dummies. All columns are estimated by two-stage least squares. Excluded instruments are the alternative permanent income measure and its interactions with dummy variables for mothers' marital and primary earner statuses. Standard errors are clustered at the children's level and reported in parentheses.
* and ** indicate statistically significant at the 10% and 5% levels.

B.8 Birth and Prenatal Characteristics

We examine whether birth and prenatal characteristics – birth order, gestation length, birth weight, and birth spacing among siblings – affect our estimates of the impact of maternal unemployment on children's future wages. Including birth spacing is motivated by evidence from Dougan et al. (2025), who show that the effectiveness of the Infant Health and Development Program (IHDP) depends on whether a child is a twin and, more broadly, on the spacing between births. As shown in Table B8, controlling for these factors does not alter the estimated negative and statistically significant effect of maternal unemployment. Most birth-related controls are small and insignificant, except for sibling status, which shows a modest positive effect. These results indicate that early-life conditions do not confound our main finding.

Table B8: Birth and Prenatal Characteristics

	(1) log(wage)	(2) log(wage)	(3) log(wage)	(4) log(wage)	(5) log(wage)	(6) log(wage)
OLF	-0.035	-0.036	-0.040	-0.044*	-0.037	-0.044
	(0.026)	(0.026)	(0.027)	(0.027)	(0.026)	(0.027)
UNEMP	-0.213**	-0.214**	-0.221**	-0.231**	-0.216**	-0.227**
	(0.078)	(0.078)	(0.081)	(0.079)	(0.078)	(0.082)
Permanent Income	0.103**	0.108**	0.099**	0.100**	0.111**	0.109**
	(0.024)	(0.026)	(0.025)	(0.025)	(0.026)	(0.027)
Birth order of child		0.010				0.005
		(0.007)				(0.008)
Length of gestation (weeks)			0.004			0.003
			(0.003)			(0.003)
Birth weight (ounces)				0.000		0.000
				(0.000)		(0.000)
Has siblings					0.058**	0.050*
					(0.028)	(0.029)
Has siblings=1 × Birth space					0.002	0.001
					(0.002)	(0.002)
Educ Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Mom Educ Dummies	Yes	Yes	Yes	Yes	Yes	Yes
Mom AFQT	Yes	Yes	Yes	Yes	Yes	Yes
Remaining Unemp	Yes	Yes	Yes	Yes	Yes	Yes
F statistic	50.051	44.996	46.226	46.400	41.934	35.840
Observations	7,713	7,713	7,214	7,409	7,713	7,068
R2	0.273	0.272	0.277	0.271	0.273	0.275

Note: See Tables 5 for the definition of mothers' ability control and for the construction of other variables. All columns are estimated by two-stage least squares. Excluded instruments are the alternative permanent income measure and its interactions with dummy variables for mothers' marital and primary earner statuses. Standard errors are clustered at the children's level and reported in parentheses.
* and ** indicate statistically significant at the 10% and 5% levels.

B.9 Distinguishing Between Voluntary and Involuntary Unemployment

Throughout most of the paper, we have examined two labor market statuses: unemployment and non-participation in the labor force. Unemployment is usually involuntary and caused by external factors beyond an individual's control; however, non-participation can be either voluntary or involuntary. For example, non-participation is voluntary if mothers choose not to work for personal reasons, such as caring for children or other family members. It can be involuntary if mothers are not employed and have stopped looking for work due to reasons beyond their control, such as inability to find suitable employment, lack of job opportunities, or disability.

Some of the mothers in our sample might have self-selected to not participate in the labor market, raising concerns about the interpretation of the coefficient on the non-participation measure. In this subsection, we identify the effect of exposure to involuntary labor-market non-participation on children's outcomes. We combine our unemployment and non-participation exposure measures into a single measure of non-employment exposure and instrument it with children's exposure to maternal employment in cyclical industries.

The idea is that mothers who work in more cyclical industries are more likely to experience involuntary job loss due to factors beyond their control. We interpret a mother's non-employment predicted by her industry's cyclical exposure as the involuntary portion of her non-employment. To construct instruments for this exercise, we follow these steps: (1) we calculate a measure of cyclical sensitivity β_i^e for each industry i, (2) using the NLSY labor history array, we associate each job with its industry's measure of cyclical sensitivity, (3) we multiply the cyclical sensitivity measure by a business cycle indicator for each month, and (4) we take the average cyclical sensitivity that each child was exposed to during childhood.

We use two measures of cyclical sensitivities of industries. First, we follow the method of McLaughlin and Bils (2001) and project the industry i employment E_{it} on aggregate employment E_t and a cubic trend,

$$\ln(E_{it}/E_t) = a_i + a_{1i}t + a_{2i}t^2 + a_{3i}t^3 + \beta_i^e \ln E_t + e_{it}\ . \tag{5}$$

Our measure of industry i's cyclical sensitivity is β_i^e. We estimate equation (5) for each industry i in the first difference. The employment variables come from the Current Employment Statistics (CES) data, a survey conducted monthly by the Bureau of Labor Statistics (BLS). We use three-digit industries in the estimation. Our time series spans from 1972 until 2019. We give a more detailed data description in the Appendix A.

Our second measure of industries' cyclical sensitivities is the durability of the goods associated with them. According to consumer theory, the durability of goods should predict the cyclical behavior of expenditures on these goods. This is because durable goods require substantial investment to increase their stock, with small increases in stock potentially leading to a proportionally larger increase in spending. Consequently, the demand for durable goods is highly sensitive to the economic cycle. This prediction is confirmed by Bils and Klenow (1998) and Bils, Klenow, and Malin (2013). We utilize durability measures for seventy goods, as constructed by Bils et al. (2013). These measures are derived from data sourced from the US National Income and Product Accounts (NIPA) and estimates provided by an insurance company.

We use two instruments for each cyclical measure. The first instrument is the job's cyclical sensitivity, where simply working in a more cyclical job is assumed to predict higher involuntary non-employment, regardless of business cycle conditions. The second instrument is the job's cyclical sensitivity interacted with a business cycle measure. For our baseline estimate, we use annual real GDP growth as our measure of the business cycle, where working in a cyclical job during periods of negative growth is assumed to predict involuntary non-employment.

In Table B9, Column 2 reports results using the job's cyclical sensitivity and its interaction with the GDP growth for predicting involuntary non-employment, while Column 3 uses the durability measure and its interaction with the GDP growth. Column 4 uses the job's cyclical sensitivity and the durability measure jointly. For comparison, Column 1 shows the results without instrumenting for involuntary non-employment. The coefficients from the instrumented regressions are significantly larger than the non-instrumented estimates. Moreover, the coefficients from the instrumented regressions are statistically significant when using the job's cyclical sensitivity as an instrument in Column 2. The specification that only uses the durability measure is not significant potentially because of large standard errors driven by a weak-IV problem. However, the point estimate is in line with the other columns.

The coefficient on non-employment exposure in Table B9, Column 4 is -0.241, similar to the coefficient of -0.207 on unemployment exposure in Table 5, Column 5. This stark similarity when accounting for involuntary non-participation implies that maternal involuntary non-employment also has scarring effects on children's future labor market outcomes. Specifically, under the assumption that all non-employment is involuntary, these results suggest that a child exposed to one standard deviation higher involuntary maternal non-employment is estimated to experience a 7.0% reduction in adult wages. Lastly, Table B9, Column 5 reports the effect of maternal non-employment on children's employment probability.

Table B9: Using Exposure to Cyclical Industries to Disentangle Voluntary and Involuntary OLF: Effects on Wages

	(1) log(wage)	(2) log(wage)	(3) log(wage)	(4) log(wage)	(5) emp.
OLF + UNEMP	-0.049*	-0.171*	-0.060	-0.110	-0.182**
	(0.026)	(0.101)	(0.099)	(0.092)	(0.083)
Permanent Income	0.103**	0.055	0.101**	0.081**	-0.010
	(0.025)	(0.045)	(0.044)	(0.041)	(0.033)
Inst. for Measurement Error	Yes	Yes	Yes	Yes	Yes
Cyclical-Job Measure		Yes		Yes	Yes
Durability Measure			Yes	Yes	Yes
F statistic	50.357	9.791	10.252	8.806	7.222
Observations	7,527	7,527	7,527	7,527	19,486
R2	0.270	0.270	0.271	0.272	0.089

Note: OLF + UNEMP are our exposure measures to maternal non-employment. See equation (1) for construction details. Permanent Income is in $10,000s (discounted present value) as of birth year. See equation (2) for construction details. Controls include dummy variables for children's race, gender, and educational attainment, a cubic polynomial in children's age, dummy variables for mothers' marital and primary earner statuses, mothers' ability controls, and fixed effects for the survey year. See Tables 5 and 5 for the definition of mothers' ability control. All models are estimated by two-stage least squares. Excluded instruments used in all Columns are the alternative permanent income measure and its interactions with dummy variables for mothers' marital and primary earner statuses. Columns 2, 3, and 4 use different measures of exposure to cyclical industries as additional instruments. See text for details. Standard errors are clustered at the children's level and reported in parentheses. The F statistic is the Kleibergen-Paap F statistic.
$^{+}$, *, and ** indicate statistically significant at the 15%, 10%, and 5% levels.

B.10 Other Labor Market Outcomes: Occupation Return and Risk

We documented that exposure to maternal unemployment and labor-market non-participation predicts children's lower earnings. It is plausible to imagine that a child who is exposed to maternal unemployment self-selects into safer occupations, presumably because the child might develop a risk aversion against earning risk. Hegarty (2022) finds evidence of the exact mechanism using the Panel Study of Income Dynamics (PSID). She construct a measure of lifetime earnings risk for 22 occupations and documents that parental layoffs are correlated with children earning less in their early careers and working in occupations with lower risk.

In this subsection, we document that children with more exposure to maternal unemployment work in low-risk occupations, but we do not find that these occupations have low returns. We measure occupational earning return and risk using Mincer equation regressions following Bonin, Dohmen, Falk, Huffman, and Sunde (2007), Hartog and Vijverberg (2007), and Necker and Voskort (2014). First, we stack the March Current Population Survey (CPS) data from 1998 to 2021. We use the Autor-Dorn crosswalk to harmonize occupation codes across years. Second, we regress the logarithm of wages on a cubic polynomial in potential experience, educational attainment dummies, sex and race dummies, year-fixed effects, and occupation-fixed effects. Our measure of occupation mean returns is the estimated coefficients on the occupation dummies. Our measure of occupation risk is the standard deviation of the residuals within each occupation. Our sample includes occupations with at least 100 individuals and normalizes the measures by their standard deviation. Therefore, the regression coefficient should be interpreted as the impact of working in an occupation with one standard deviation above the average return or risk.

Table B10 shows the results when we use 3-digit occupation codes to create our measures. Columns 1 and 3 show that occupation returns are unrelated to the unemployment exposure measure. Columns 3 and 4 show that more unemployment exposure is associated with lower occupational earning risk. As mentioned, this finding is consistent with Hegarty (2022) and the mechanism that exposure to unemployment or parental layoffs during childhood leads individuals to self-select into lower-earning but safer occupations. In Column 4, we focus on individuals over 30 years old. Since we interpret the previous result as related to risk aversion, we expect a stronger effect for older workers (i.e., even lower occupational risk). Job search and career transitions take time, so older workers had more opportunities to self-select into occupations consistent with their risk preferences. Consistent with this interpretation, we find a stronger effect for this subgroup.

Our baseline measure of occupational earning risk is constructed using 3-digit occupations. Table B11 uses 2-digit occupations codes. In Columns 1 and 3, we continue to find occupation returns that are unrelated to the unemployment exposure measure. In Columns 3 and 4, we observe that the impact of unemployment exposure is still negative but not significant. Moreover, the result is stronger for the older sample but, again, not significant. We conclude that having finer occupation codes is essential for the documented result.

Table B10: Other Labor Market Outcomes: Earning Risk

	All Sample	Above 30 Yr	All Sample	Above 30 Yr
	(1)	(2)	(3)	(4)
	3d-Occ Return	3d-Occ Return	3d-Occ Risk	3d-Occ Risk
OLF	-0.007	-0.035	0.049	0.028
	(0.015)	(0.025)	(0.070)	(0.111)
UNEMP	0.044	0.057	-0.520**	-0.960**
	(0.051)	(0.085)	(0.210)	(0.269)
Permanent Income	0.028**	0.014	0.009	-0.028
	(0.013)	(0.024)	(0.060)	(0.098)
Educ Dummies	Yes	Yes	Yes	Yes
Mom Educ Dummies	Yes	Yes	Yes	Yes
Mom AFQT	Yes	Yes	Yes	Yes
Add. unemp	Yes	Yes	Yes	Yes
F statistic	49.403	18.169	48.430	18.066
Observations	7,517	2,191	7,501	2,194
R2	0.224	0.183	0.030	0.047

Note: See text for details how how earning risk is constructed. See Tables 5 for the definition of mothers' ability control and for the construction of other variables. All columns are estimated by two-stage least squares. Excluded instruments are the alternative permanent income measure and its interactions with dummy variables for mothers' marital and primary earner statuses. Standard errors are clustered at the children's level and reported in parentheses.
* and ** indicate statistically significant at the 10% and 5% levels.

Table B11: Other Labor Market Outcomes: Earning Risk

	All Sample	Above 30 Yr	All Sample	Above 30 Yr
	(1)	(2)	(3)	(4)
	2d-Occ Return	2d-Occ Return	2d-Occ Risk	2d-Occ Risk
OLF	-0.004	-0.035	0.070	0.034
	(0.013)	(0.024)	(0.066)	(0.109)
UNEMP	0.010	0.037	-0.322	-0.480
	(0.050)	(0.083)	(0.228)	(0.310)
Permanent Income	0.019	0.015	0.084	0.082
	(0.012)	(0.024)	(0.060)	(0.091)
Educ Dummies	Yes	Yes	Yes	Yes
Mom Educ Dummies	Yes	Yes	Yes	Yes
Mom AFQT	Yes	Yes	Yes	Yes
Add. unemp	Yes	Yes	Yes	Yes
F statistic	50.051	18.731	50.048	18.731
Observations	7,713	2,248	7,711	2,248
R2	0.207	0.163	0.025	0.054

Note: See text for details how how earning risk is constructed. See Tables 5 for the definition of mothers' ability control and for the construction of other variables. All columns are estimated by two-stage least squares. Excluded instruments are the alternative permanent income measure and its interactions with dummy variables for mothers' marital and primary earner statuses. Standard errors are clustered at the children's level and reported in parentheses.
* and ** indicate statistically significant at the 10% and 5% levels.

B.11 Additional Results on Mothers' Time of Use

Table B12: Average Number of Minutes per Mother' Status and Family Income

	Emp	Unemp	OLF
Total Time Spent on All Activities	1440.00	1440.00	1440.00
Caring for and Helping Household Members	109.38	162.20	205.07
Caring for and Helping Children	88.16	138.46	179.15
Education-Related Activities for Children	10.28	17.50	23.12
Health-Related Activities for Children	3.07	5.80	4.98
Other Caring Activities for Children	74.80	115.15	151.05
Caring for and Helping Non-Household Members	6.55	14.21	11.11
Working and Work-Related Activities	385.55	38.41	4.90
Leisure and Social Activities	173.24	271.58	258.46
Purchasing Goods and Eating	102.14	135.82	132.13
Personal Care and Household Activities	635.74	761.39	774.72
Educational Activities	7.43	22.38	19.28
Other and Communication Activities	19.96	34.02	34.33

Note: The sample consists of women between 25 and 50 who reported having children under 18 living in the household. We look at the days of the week and non-holidays. Time allocation categories are the major BLS aggregate categories. Each cell represents averages. We use survey sample weights and construct additional weights to correct for differences in family income across employment status groups.

Table B13: Average Number of Minutes per Mother' Status and School Groups

	Emp	Unemp	OLF
Total Time Spent on All Activities	1440.00	1440.00	1440.00
Caring for and Helping Household Members	106.88	161.73	204.20
Caring for and Helping Children	85.93	138.58	178.52
Education-Related Activities for Children	10.24	18.08	22.77
Health-Related Activities for Children	2.97	5.75	5.17
Other Caring Activities for Children	72.72	114.74	150.58
Caring for and Helping Non-Household Members	6.76	14.17	11.37
Working and Work-Related Activities	384.04	37.10	4.93
Leisure and Social Activities	174.26	271.48	259.80
Purchasing Goods and Eating	101.81	132.47	131.46
Personal Care and Household Activities	639.88	761.37	774.19
Educational Activities	6.78	27.76	19.99
Other and Communication Activities	19.59	33.91	34.06

Note: The sample consists of women between 25 and 50 who reported having children under 18 living in the household. We look at the days of the week and non-holidays. Time allocation categories are the major BLS aggregate categories. Each cell represents averages. We use survey sample weights and construct additional weights to correct for differences in education levels across employment status groups.

Table B14: Average Number of Minutes per Mother' Status, Age of the Youngest Child, and the Number of Children

	Emp	Unemp	OLF
Total Time Spent on All Activities	1440.00	1440.00	1440.00
Caring for and Helping Household Members	113.85	153.17	183.77
Caring for and Helping Children	92.25	130.47	158.66
Education-Related Activities for Children	10.33	18.68	22.74
Health-Related Activities for Children	3.22	4.63	4.70
Other Caring Activities for Children	78.70	107.16	131.21
Caring for and Helping Non-Household Members	6.46	14.72	12.62
Working and Work-Related Activities	383.45	36.86	5.33
Leisure and Social Activities	171.74	277.99	271.00
Purchasing Goods and Eating	103.09	125.94	131.12
Personal Care and Household Activities	634.10	771.80	781.20
Educational Activities	7.24	28.13	21.12
Other and Communication Activities	20.08	31.40	33.84

Note: The sample consists of women between 25 and 50 who reported having children under 18 living in the household. We look at the days of the week and non-holidays. Time allocation categories are the major BLS aggregate categories. Each cell represents averages. We use survey sample weights and construct additional weights to correct for differences in the age of the youngest child and the number of children across employment status groups.

B.12 Local Labor Market and Mobility

Chetty et al. (2014b), Chetty et al. (2016), and Chetty et al. (2024) document the importance of neighborhood environments in shaping children's long-term outcomes. To account for this channel, we use restricted-use County Geocode data to ensure that our findings are not simply driven by geographic location. While our data is limited to the county level–less granular than the neighborhood-level variation emphasized in prior work–it still allows a meaningful examination of the local environment. These geocode files provide detailed locational information on survey respondents, including their county of residence at various points in time. This allows us to complement our analysis of maternal unemployment exposure with an investigation into how county-level conditions influence children's future labor market outcomes.

We construct three measures of the local environment during childhood: (1) Exposure to County Unemployment, defined as the average county-level unemployment rate during the child's formative years; (2) Exposure to County Income, measured using per capita personal income; and (3) Number of Counties Lived In, capturing the extent of residential mobility, which may reflect instability and have independent effects on child development. County unemployment data come from the Bureau of Labor Statistics' Local Area Unemployment Statistics (LAUS), which provide monthly estimates of labor force conditions at the county level. County income data are obtained from the Bureau of Economic Analysis' Regional Economic Accounts, which report annual measures of personal income and population.

Table B.12 shows that county-level unemployment and income are both predictive of children's future wages. However, they are insufficient to account for the negative impact of maternal unemployment exposure, suggesting that the mechanisms at play go beyond local labor market conditions. Columns 1 and 3 show the baseline results for comparison.

Table B15: Robustness: Controlling for Local Labor Market and Mobility

	(1) log(wage)	(2) log(wage)	(3) log(wage)	(4) log(wage)
OLF	-0.037	-0.056**	-0.035	-0.033
	(0.026)	(0.026)	(0.026)	(0.026)
UNEMP	-0.216**	-0.198**	-0.213**	-0.211**
	(0.078)	(0.077)	(0.078)	(0.078)
Permanent Income	0.099**	0.067**	0.103**	0.103**
	(0.024)	(0.026)	(0.024)	(0.024)
County Unemp		0.011**		
		(0.003)		
County Income		0.281**		
		(0.037)		
Number of moves				-0.004
				(0.006)
Educ Dummies	Yes	Yes	Yes	Yes
Mom Educ Dummies	Yes	Yes	Yes	Yes
Mom AFQT	Yes	Yes	Yes	Yes
Remaining Unemp	Yes	Yes	Yes	Yes
F statistic	49.423	44.010	50.051	50.100
Observations	7,652	7,652	7,713	7,713
R^2	0.273	0.289	0.273	0.273

Notes: OLF and UNEMP capture exposure to maternal non-participation and unemployment, respectively (see equation 1). Permanent Income is measured in \$10,000s as the discounted value at birth year (see equation 2). County-level unemployment and income are included to account for local labor market conditions. All models control for children's demographics and education, maternal characteristics, and survey-year fixed effects. Standard errors clustered at the child level are shown in parentheses. The F statistic is the Kleibergen-Paap statistic.
* and ** indicate statistically significant at the 10% and 5% levels.

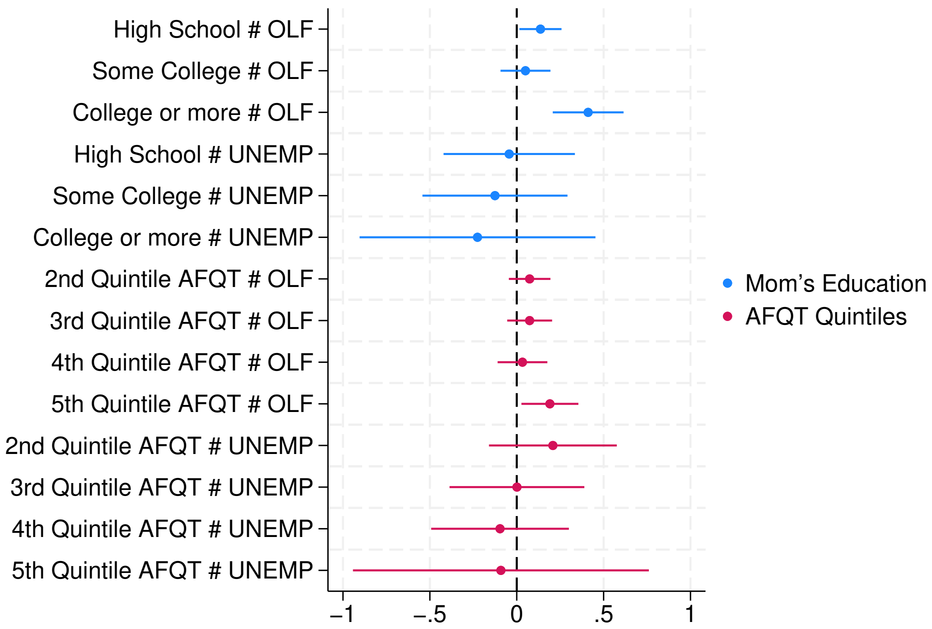
C Additional Figures

C.1 Heterogeneous Effect by Mother's Ability

We also check whether maternal unemployment has different effects on the children's future wages depending on the mother's education and abilities by plotting the coefficients for the interaction of educational attainment dummies and AFTQ scores with both exposure measures. Those coefficients are presented in Figure C1.

Overall, we do not see any significant heterogeneity in the effect of maternal unemployment. While all the interaction terms are statistically insignificant, exposure to maternal unemployment seems more detrimental when the mother has a college degree than when she is less educated. When the mother is out of the labor force, we find that children whose college-educated mothers are out of the labor force have higher future wages than those whose mothers are also out of the labor force but not college-educated.

Figure C1: Heterogeneous Effect: Measures of Mother's Ability



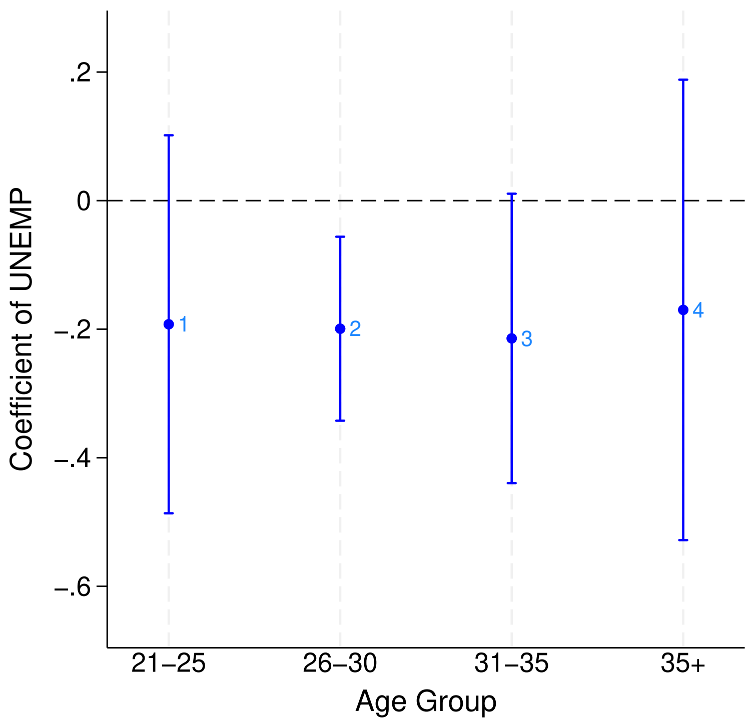
Note: This figure plots the coefficients from estimating equation 3 with children's wages as outcomes, augmented with the interaction terms between our measures of exposure to maternal non-employment (OLF and UNEMP) and measures of mother's cognitive abilities (education and AFQT quintiles). Each dot represents a point estimate of the effect of a variable displayed on the left-hand side on children's future wages, with the confidence interval plotted around. The magnitudes of the point estimates and the confidence intervals can be determined by looking at the X-axis.

C.2 Persistent Effect of Unemployment Over Age Groups

We also check how the impact of maternal unemployment varies across different age groups. The goal is to determine whether the effects of experiencing unemployment during childhood persist as individuals grow older or if they diminish over time. We estimate the effect of unemployment by dividing the sample into four age groups: (i) 21-25 years, (ii) 26-30 years, (iii) 31-35 years, and (iv) 35+ years. We estimate using our specification corrected for measurement error and with proxies for the mother's quality.

Figure C2 presents the estimated coefficients across the four age groups, with confidence intervals represented by vertical error bars. The estimated effect of unemployment is negative across all age groups and has a similar magnitude, with no clear upward or downward trend over time. The coefficient is insignificant in some specifications because of the reduced number of observations.

Figure C2: Persistent Effect of Unemployment Over Age Groups



Note: This figure plots the coefficients of exposure to maternal unemployment on children's wages. Each dot represents a point estimate of the effect of unemployment at a given age group on children's future wages, with confidence intervals displayed around the estimates. The magnitude of the point estimates and the width of the confidence intervals can be interpreted by referring to the Y-axis.

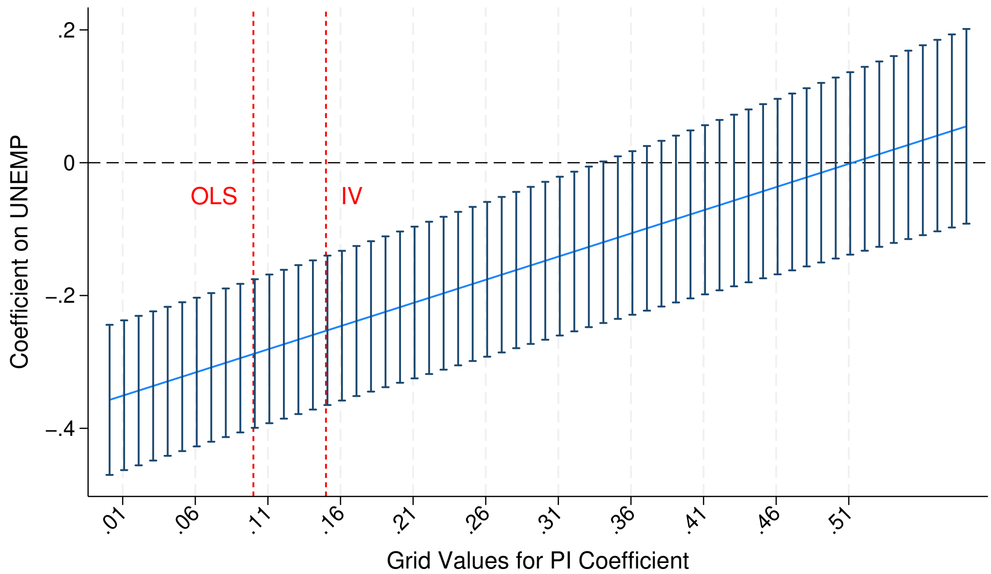
C.3 Assessing the Downstream Impact of Unemployment Beyond Income

Maternal unemployment impacts the outcome directly and through income. So, we control for a measure of permanent income to estimate the impact of unemployment not explained by the income channel. However, for that, it is crucial to estimate the coefficient on permanent income correctly. We deal with this concern first using instrumental variable estimation to correct for measurement error in permanent income. Additionally, we conduct a constrained regression where the coefficient on permanent income is fixed at different values within a pre-specified grid. This approach allows us to assess how the estimated impact of maternal unemployment changes as we impose different assumptions about the true value of the income coefficient.

Figure C3 shows that, if the true PI coefficient were large enough, the estimated impact of unemployment could approach zero—indicating that income fully accounts for any observed effects of unemployment. In particular, the graph plots the estimated coefficient on UNEMP (y-axis) as a function of different fixed values of the PI coefficient (x-axis). Two vertical lines represent the OLS and IV estimates of the PI coefficient.

For the estimated effect of unemployment to be fully accounted for by income (i.e., for the unemployment coefficient to reach zero), the true PI coefficient would need to be around 0.5. This value is five times larger than the OLS estimate and more than three times larger than the IV estimate. This suggests that income alone cannot fully explain the effects of unemployment unless one assumes an implausibly large coefficient on permanent income. In other words, unemployment likely has an independent impact beyond its effect through income. This highlights the importance of considering non-income channels when studying the consequences of unemployment.

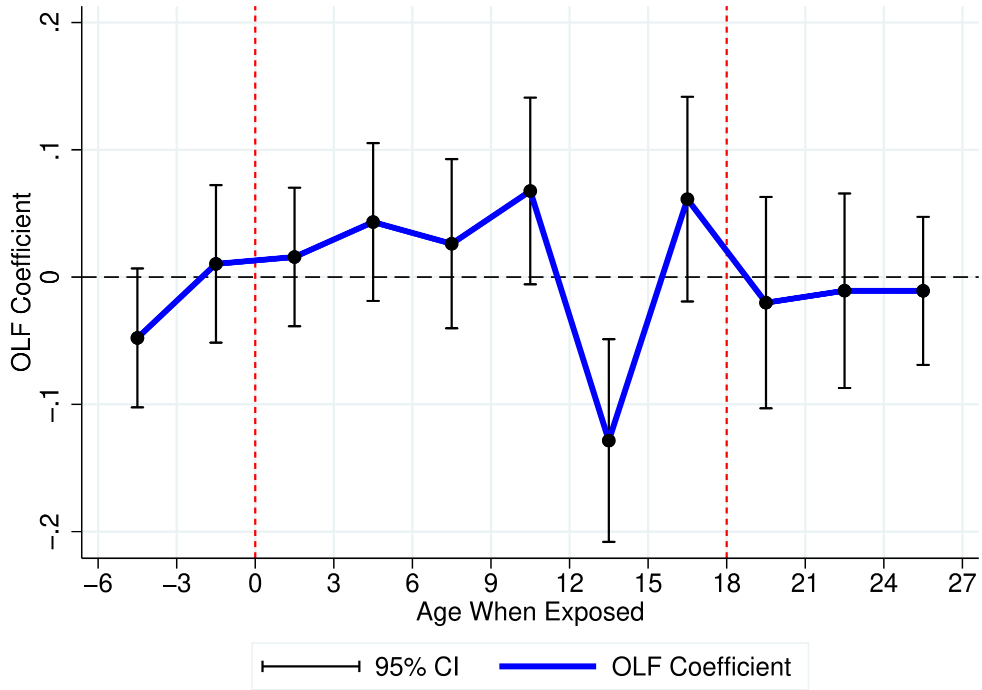
Figure C3: Assessing the Downstream Impact of Unemployment Beyond Income



Note: This figure presents results from a constrained regression exercise where the coefficient on permanent income (PI) is fixed at different values along a predefined grid. By imposing these constraints, we examine how the estimated coefficient on unemployment (UNEMP) changes. This approach helps assess the extent to which income alone accounts for the observed impact of unemployment.

C.4 Impact of Maternal Non-Participation on Wages by Childhood Stage

Figure C4: Impact of Maternal Non-Participation on Wages by Childhood Stage



Note: This figure plots the estimated effect of maternal non-participation exposure on children's log wages at different age groups. The coefficients are obtained from an instrumental variables regression where log wages are regressed on non-participation exposure measures, three unemployment measures, three permanent income measures, child demographics (race, sex, age polynomials, education), maternal characteristics (marital status, primary earner status), and maternal quality proxies (AFQT, maternal education). We also create three permanent income instruments and interact them with maternal characteristics. The plot shows point estimates with 95% confidence intervals, adjusting for clustering at the individual level. The x-axis represents the child's age at the time of non-participation exposure, with negative values indicating exposure before birth. The vertical dashed line at age 0 marks birth, and the line at age 18 marks adulthood.