Growing up with an Unemployed Mother*

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Abstract

Job losses negatively affect children's labor market outcomes through decreases in family income. Since unemployed parents have more time available to invest in their children, the effects of parental unemployment on children's future outcomes are ambiguous after accounting for this drop in income. Using NLSY79 and NLSY79-CYA, we show that the total amount of time a mother spends unemployed throughout her child's childhood has direct negative effects on the child's future wage and employment probability, even conditional on family income. By contrasting these results with the weaker effects of mothers being out of the labor force and instrumenting for involuntary maternal non-employment, we suggest that the effects might be causal. We further show that maternal unemployment negatively impacts the quality of the home environment and that unemployed mothers allocate very little additional time to educating their children.

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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 mental health problems and large and persistent declines in lifetime income for workers, as well as lower educational attainment and worse labor outcomes for workers' children. The literature has documented the harmful effects of parental job loss on children's labor outcomes by comparing displaced workers with non-displaced workers, who are otherwise similar. While this approach suggests a causal relationship between job loss and children's outcomes, it does not distinguish the effect of income loss from the other potential effects of having an unemployed parent. Moreover, it does not distinguish between parents who spent a short period unemployed and those who experienced longer unemployment duration or multiple unemployment spells.

In this paper, we study the long-term effects of maternal unemployment on children's labor market outcomes. To do so, we construct a measure of children's exposure to maternal unemployment as the fraction of their childhood that their mothers spent unemployed. Importantly, our measure captures the intensity of mothers' unemployment, allowing us to differentiate someone who lost a job once and immediately found a new one versus someone who has been consistently unemployed. Also, our measure 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 employment probability and future 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. Our results show that mothers' inability to find a job has a direct causal effect on children's labor market outcomes by contrasting the unemployment exposure results with the weaker one of having mothers out of the labor force and using the exposure to cyclical industries as an instrument for involuntary non-participation. Finally, we document that maternal unemployment is associated with a worse home environment and that unemployed mothers spend very little of their additional time investing in their children's human capital. Both of these results are potential mechanisms that help to explain the persistent scarring effects of maternal unemployment.

We use data from 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 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.

More time spent with an unemployed mother when growing up reduces a child's employment probability and lowers their future wage. A child who is one standard deviation above the mean exposure to maternal unemployment (approximately 67 additional weeks of his/her childhood 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 reduces family income and, consequently, reduces the amount parents invest in children, especially if budget constraints are binding. We control for the family income and show that it accounts only for a part of the documented negative relation. 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.[1] This result suggests that maternal unemployment has scarring effects beyond lower income. Moreover, we show that this scarring effect of unemployment cannot be explained by children's education attainment, even though maternal unemployment does negatively affect it.

We show that these scarring effects are not explained by a correlation between the amount of time a mother spends unemployed and her skills in investing in the child's human capital or parenting skills. To evaluate this possibility, we control for mothers' education levels, cognitive ability measures, and the time the mother spent unemployed outside of the first 18 years of the child. After accounting for these controls, most of the scarring effect of unemployment remains unexplained. These results suggest that the correlation between work skills and parenting skills is not strong enough to generate a negative relation between exposure to maternal unemployment and children's future wages and employment probability.

To better establish a causal link between maternal unemployment and children outcomes, we instrument the exposure to maternal non-employment using the exposure to maternal employment in cyclical industries. The idea is that mothers working in a more cyclical industry are more likely to suffer involuntary non-employment, whether this is unemployment or involuntary non-participation in the labor market. The identifying assumption is that exposure to maternal employment in cyclical industries predicts exposure to maternal unemployment and explains children's future outcomes only through maternal unemployment. The instrumented results show an even stronger negative effect of maternal non-employment on children's wages, suggesting that the fact

[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.

that mothers cannot find work during their children's childhood hurts children's future prospects.

Lastly, we investigate mechanisms behind the scarring effect of unemployment. First, we show that maternal unemployment has a similar negative effect on wages, regardless of whether the child experienced it before or after age 12. Second, we look at different assessment tests available in the NLSY-CYA to document how maternal unemployment impacts children's development. We document indeed that maternal unemployment harms children's home environment but does not seem to affect their cognitive development. Possibly, the anxiety and stress that mothers face when not having a job might harm their children. Third, we use the American Time of Use Survey (ATUS) to document that mothers allocate most of the extra time available after unemployment to leisure. The increase in activities related to children's education is minimal.

Roadmap. Section 2 describes our measure of exposure to maternal unemployment and family permanent income. Section 3 describes how we associate maternal unemployment exposure with children's outcomes. Section 4 presents the facts on the impact of maternal unemployment on children's labor market outcomes. Section 5 concludes. The appendix contains additional empirical results.

Related Literature

Our paper is related to the research on the costs of losing a job and being unemployed. Jacobson, LaLonde, and Sullivan (1993) and Stevens (1997) document that job loss and unemployment lead to persistent drops in earnings, even after reemployment. Unemployment also seems to have negative effects beyond income losses, such as deterioration of mental health (Cygan-Rehm, Kuehnle, and Oberfichtner, 2017).

A number of papers further document that unemployment affects not only the workers themselves but also their children's education and future labor outcomes. For example, Oreopoulos, Page, and Stevens (2008) show that job loss leads to a decline in future wages of displaced workers' children in Canada, and Fradkin, Panier, and Tojerow (2019) found that children in Belgium whose parents lost their jobs before the children entered the labor market worked 9% more during their first three years in the workforce. These papers use event studies to document the effects. We revisit the effects of parental job loss on children's future labor market outcomes by using a measure that captures a child's exposure to maternal unemployment while growing up.

Multiple potential mechanisms explaining the connection between parental unemployment and children's labor market outcomes have been explored in the literature. Coelli (2011) documents that the negative effect of job loss on children's future wages is at least partially driven by lower family income and its effect on children's education. The author shows that children who are in high school at the time of parental job loss are less likely to enroll at a university or community college. Hilger (2016), however, documents that while parental layoffs dramatically reduce family income, they do not significantly affect college enrollment, college quality, and early career earnings. Rege, Telle, and Votruba (2011) use Norwegian data to document that paternal job loss negatively impacts children's school performance, although they do not find any significant effect for maternal job loss. They argue that their results are consistent with mental distress experienced by displaced workers. We contribute to this literature by showing that the reduction in family income and the education channel are not enough to explain the relationship between unemployment and children's labor outcomes.

Our paper also fits into a broader context of the roles that different investment inputs play in a child's human capital formation (Cunha, Heckman, and Schennach, 2010; Caucutt, Lochner, Mullins, and Park, 2023) and is specifically related to the trade-off between parental income and time investment. Working less implies less family income, which could be invested in childcare and education, but it also gives parents more time to spend with their children. Indeed, parental time has been shown to be an important input in a child's development (Caucutt et al., 2023).

The empirical evidence on the trade-off between income and time is explored in a number of papers using Earned Income Tax Credit expansion, including Bastian and Lochner (2020) and Agostinelli and Sorrenti (2022). Bastian and Lochner (2020) show that while EITC encourages labor participation among single mothers and reduces the overall time the mothers spend with their kids, almost none of the reduction comes from the time spent on investing in children's human capital, suggesting that maternal employment benefits children's development through the increase in income and does not decrease the time investment. Agostinelli and Sorrenti (2022), however, find that EITC expansion hurts the behavioral and cognitive indicators of children due to the decrease in time children spend with their mothers. They document that EITC is associated with a decrease in the quality of the interactions between the mothers and the children, with results especially pronounced among disadvantaged families who do not have access to high-quality childcare. In our paper, we provide suggestive evidence that maternal employment is positively correlated with the quality of the home environment, even after controlling for income, and that it does not come at the expense of the time spent with the child.

Lastly, similar to our approach, Blau and Grossberg (1992) measure the maternal time available to invest in children using the share of weeks that mothers worked during their children's first years. They also control for family income to isolate the impact of labor supply from market inputs. Our study differs by focusing on the impact of different labor market statuses, particularly unemployment. Also, they look at mothers' labor supply during the first four years of a child and measure the impact of mothers' labor supply on children's cognitive development using the Peabody Picture Vocabulary Test. We look at their 18 years of childhood and focus on the impact on labor market outcomes, such as their wage rate and employment probability. We also look at measures of cognitive development.

2 Identifying the Impact of Maternal Unemployment on Children's Labor Market Outcomes

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 containing comprehensive information on the labor market status of mothers and tracking their offspring as they enter the workforce. Additionally, 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 The NLSY 79 and NLSY79-CYA Data

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 from January 1, 1978, to the last interview date at a weekly frequency. 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 job satisfaction.

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 as their highest educational attainment 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 Measuring 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. However, this approach struggles to differentiate the effect of the time spent unemployed and makes it hard 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. The labor force status array contains weekly information on the respondent's labor market status, whether "employed," "unemployed," "out of the labor force," and "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:

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

In the denominator, we count the number of weeks during which the mother reported being unemployed in the labor force status array. Here, $\textit{mother}(i)$ is a function that denotes the identifier of child i's mother, and $\textit{labor status}_{\textit{mother}(i),t}$ is a variable indicating the labor market status of the mother 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.

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).[2] As the last step, we average these ratios over the 18 years of childhood to construct a measure representing the maternal unemployment exposure.

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.

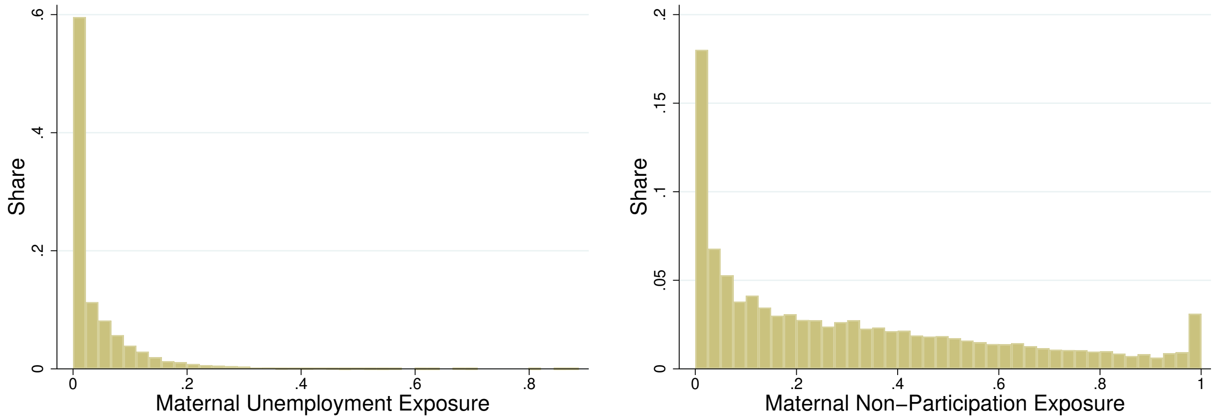
2.3 Measuring Family Permanent Income

Unemployment directly affects families through lower labor income. 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 is inspired by Carneiro and Heckman

[2]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, so information for the years it was collected is unavailable.

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.

(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 in which the child was born.[3] 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.

We calculate per capita income by dividing total net family income 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. For respondents for whom this variable is unavailable, we manually create a family income measure. 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.[4] 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,

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

[4]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.

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 years of the 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 Measuring Mothers' Unobserved Heterogeneity

We are interested in the impact of maternal unemployment on children and, in particular, their labor market outcomes. For that, we construct a measure of children's exposure to maternal unemployment during their childhood. A concern with this approach is whether this measure captures the effect of latent mothers' characteristics as well as 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 may at the same time be the ones who spend more time unemployed because of some cognitive and personal characteristics, e.g., lack of education, irresponsibility, absent-mindedness, etc.

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

We first use mothers' education attainment as a proxy for unobserved quality. The assumption is that the more educated a mother is, the better she is at educating her children and less likely to experience unemployment. Second, we use as a proxy 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 considering mothers' education and their AFQT score, 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. Additionally, we construct measures of children's exposure to unemployment five years before their birth and during five years of their adulthood. None of these measures can account for the negative association between maternal unemployment and children's labor market outcome.

3 The Impact of Maternal Unemployment on Children's Labor Market Outcome

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 we examine whether the effects of maternal non-employment are in fact non-linear.

3.1 The Impact on 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 stands for 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 permanent income when young 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, this means that our exercise is a forecasting exercise, where these measures obtained when the child was younger than 18 years old are used to predict future outcomes when they are in their working years.

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

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 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' worked hours.

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 a set of controls to capture mothers' latent quality. The logic behind these controls is explained in Subsection 2.4. 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 Dealing with Measurement Error

As mentioned above, the measurement error in family permanent income is one of the concerns for our analysis.[5] 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 and the wage rate available for each job. Weekly earnings are defined as hours worked that week times the wage rate for 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 a dummy that captures whether the mother 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

[5] 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.

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' quality are uncorrelated with the alternative permanent income measure. We deal with the latter by including controls that capture mothers' latent quality.

4 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 relations are robust to controlling for mothers' unobserved heterogeneity and measurement error. We do not find any significant effect of maternal unemployment on the child's workweek.

4.1 The Impact on Labor Market Outcomes

First, we estimate equation (3) without including permanent income to document how maternal labor status affects the labor market outcomes of their children. We look at the effects on total earnings, wages, hours worked, and employment probability. In Appendix B, we also show results for the riskiness of chosen occupations.

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 early 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.[6] The estimated coefficients on the unemployment and labor-force participation exposure measures on wages are -0.50 (standard deviation 0.09) and -0.16

[6]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 three 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. In Table B1, we show that the results are robust regardless of how we select which match to include in our sample.

(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.[7]

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	-0.663**	-0.499**	0.036	-0.340**
	(0.152)	(0.085)	(0.034)	(0.065)
Observations	8,682	8,682	8,682	22,920
R2	0.166	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.

In Appendix B, Tables B2 and B3 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 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

[7] In Appendix B, we show that the effect of the mother being out of the labor force depends on the gender of the child. Having their 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 Galassi, Koll, and Mayr (2021).

mechanism using the Panel Study of Income Dynamics (PSID).

4.2 Scarring Effects Beyond Lower Income

Maternal unemployment can impact child outcomes by decreasing family income and, consequently, affecting parents' investment in the child's human capital. To separate the direct impact of unemployment on children, 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 information available 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.

In Table B4 of Appendix B we examine the potential non-linearity of the relationship between

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**	-0.122**	-0.093**	-0.201**	-0.184**	-0.176**
	(0.024)	(0.024)	(0.026)	(0.017)	(0.017)	(0.019)
UNEMP	-0.393**	-0.328**	-0.293**	-0.303**	-0.275**	-0.262**
	(0.085)	(0.078)	(0.078)	(0.068)	(0.067)	(0.068)
Permanent Income		0.099**	0.154**		0.032**	0.047**
		(0.010)	(0.023)		(0.006)	(0.016)
F statistic			15.972			20.392
Observations	8,377	8,377	8,377	21,737	21,737	21,737
R2	0.175	0.196	0.190	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.

non-employment and children's wages and employment probability. Table B4 shows that while the effects of maternal unemployment on wages do not exhibit strong non-linear patterns once we control for permanent income, the exposure to being out of the labor force affects children's outcomes only when it spans more than 9 years. This further supports the finding that being out of the labor force has a much weaker effect on children's wages than maternal unemployment. While any exposure to maternal unemployment negatively affects future children's wages, the results suggest that maternal unemployment for less than 1 year does not have any significant effect on the employment probability of the child.

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 measures of exposure to maternal unemployment and labor-force participation 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.

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	0.087*	-0.157**	-0.060**
	(0.045)	(0.022)	(0.014)
UNEMP	0.269**	-0.377**	-0.153**
	(0.134)	(0.074)	(0.050)
Permanent Income	-0.146**	0.088**	0.030**
	(0.055)	(0.022)	(0.014)
F statistic	12.315	15.809	15.809
Observations	3,516	7,719	7,719
R2	0.303	0.255	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.

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

	(1) log(wage)	(2) log(wage)	(3) emp.	(4) emp.
OLF	-0.091**	-0.046*	-0.174**	-0.135**
	(0.026)	(0.025)	(0.019)	(0.018)
UNEMP	-0.311**	-0.232**	-0.278**	-0.200**
	(0.080)	(0.073)	(0.068)	(0.066)
Permanent Income	0.153**	0.131**	0.046**	0.028*
	(0.023)	(0.023)	(0.016)	(0.015)
High School		0.025*		0.076**
		(0.015)		(0.012)
Some College		0.172**		0.171**
		(0.017)		(0.012)
College or more		0.356**		0.243**
		(0.021)		(0.014)
F statistic	16.004	15.329	20.226	19.493
Observations	8,016	8,016	20,857	20,857
R2	0.184	0.259	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 a negative relation between exposure to maternal unemployment and labor-force participation and a child's wage and employment probability. Unemployment and participation partially impact children's outcomes due to lower family income and worse education attainment. But, importantly, the scarring effects of unemployment and labor-market participation go beyond their impact on income and education. This scarring effect may 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 Table 5, we control for three measures of mothers' abilities to account for heterogeneity in their ability to invest in their 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 measures of mothers' abilities as controls. For comparison, Column 1 reports the results without ability controls.

Looking across Columns 2 to 4, we can see that our measures of mothers' abilities explain only a small portion of the negative effect on wages associated with exposure to unemployment. For example, when controlling for all measures in Column 4, we find that one standard deviation higher exposure is associated with -1.5% lower wages. Similarly, our measures of mothers' abilities 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. While factors such as mothers' cognitive abilities and unobserved characteristics contribute to a small part of this effect, they are far from fully accounting for it. On the other hand, in the case of the negative effect of mothers being out of the labor force, a significant fraction can be explained by mothers' abilities and characteristics. Potentially, the negative effect of mothers not participating in the labor market might be explained by these mothers tending to be less educated and not because the time they spend at home is detrimental for the child.

In Table 6, 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 measures of mothers' abilities. As in the previous table, Column 1 does not control for mother's abilities, while Columns 2-4 gradually introduce additional controls. Overall, the mothers' cognitive abilities and unobservable characteristics explain only a small part of the unemployment and labor-force participation effect. [8]

Appendix B has additional results. Table B5 extends the previous results to all outcomes analyzed throughout the paper: (1) total earnings, (2) wages, (3) weekly hours, (4) employment probability, and (5) occupation risk. Table B6 has more controls to fully account for the childhood environment. In it, we control for the mother's age at childbirth, spousal labor supply, family structure, and location. The estimated impact of maternal unemployment on adult wages increases after adding the full set of controls.

[8] Table B10 in Appendix B shows that the effects of UNEMP and OLF on the employment probability of the child depend on the child's gender. The effect of OLF is much stronger for girls than for boys, potentially reflecting transmission of the gender norms from mothers to daughters. The opposite holds for the effect of UNEMP: it is stronger for boys. We also show that there is no gender heterogeneity in the effects on wages.

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

	(1) log(wage)	(2) log(wage)	(3) log(wage)	(4) log(wage)
OLF	-0.049*	-0.035	-0.030	-0.029
	(0.026)	(0.026)	(0.026)	(0.026)
UNEMP	-0.258**	-0.245**	-0.223**	-0.207**
	(0.073)	(0.073)	(0.073)	(0.078)
Permanent Income	0.128**	0.123**	0.120**	0.120**
	(0.023)	(0.025)	(0.025)	(0.025)
Educ Dummies	Yes	Yes	Yes	Yes
Mom Educ Dummies		Yes	Yes	Yes
Mom AFQT			Yes	Yes
Remaining Unemp				Yes
F statistic	14.520	13.378	12.688	12.710
Observations	7,708	7,708	7,708	7,708
R2	0.266	0.268	0.270	0.270

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.

In Table B7, we do a placebo test by controlling for maternal labor-market statuses when children are already in adulthood and before their birth. The critical assumption in our analysis is that the mothers' labor-market statuses are driven by exogenous factors and not by an unobservable heterogeneity. A reassuring result that we find in Table B7 is that mothers' labor market statuses when children are already in adulthood or before they are born are not related to their 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. Lastly, Table B8 shows the results allowing for mother-fixed effects.[9]

[9]The NLSY's panel structure allows us to explore variation within families. Specifically, we can examine the variation between siblings who were exposed to different quantities of maternal unemployment. An interesting finding across all specifications of Table B8 is that the coefficients on unemployment and non-participation exposure measures or the permanent income measure are statistically insignificant and have the opposite signs of the results without using fixed effects. A possible explanation for this result is that siblings often share similar childhood conditions. For instance,

Table 6: Measures of Mother's Ability: Effects on Employment

	(1)	(2)	(3)	(4)
	emp.	emp.	emp.	emp.
OLF	-0.119**	-0.108**	-0.112**	-0.110**
	(0.018)	(0.019)	(0.019)	(0.019)
UNEMP	-0.156**	-0.155**	-0.163**	-0.129*
	(0.065)	(0.065)	(0.065)	(0.069)
Permanent Income	0.067**	0.073**	0.077**	0.076**
	(0.015)	(0.017)	(0.017)	(0.017)
Educ Dummies	Yes	Yes	Yes	Yes
Mom Educ Dummies		Yes	Yes	Yes
Mom AFQT			Yes	Yes
Remaining Unemp				Yes
F statistic	38.252	36.485	35.567	35.323
Observations	20,102	20,102	20,102	20,102
R2	0.087	0.087	0.087	0.088

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.

4.4 Breaking OLS's Impact into Voluntary and Involuntary OLF

Until now, 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.

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. 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.

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 measures of unemployment and non-participation exposure into a single measure of non-employment exposure and instrument it with children's exposure to maternal employment in cyclical industries.[10]

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,

$$\ln(E_{it}/E_t) = a_i + a_{1i}t + a_{2i}t^2 + a_{3i}t^3 + \beta_i^e \ln E_t + e_{it} \ . \tag{4}$$

Our measure of industry i's cyclical sensitivity is β_i^e. We estimate equation (4) for each industry i in 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

[10]We use exposure to cyclical industries as an instrument to decompose non-employment into its voluntary and involuntary components. This contrasts with the other tables in the paper in which we look at unemployment and non-participation separately. In Table B11, we divide the unemployment and non-participation exposure measures separately and instrument them with the our measures of cyclical industries exposure. The F statistics for these specifications are particularly low, indicating they suffer from weak instruments. We report the results, but they should be interpreted with caution.

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 Appendix B.9, we show results using two other measures of the cycle, NBER recession indicators and the cyclical component of log aggregate employment detrended using a cubic trend as the cycle measure.

In Table 7, 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 Columns 2 and 4. 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 7, 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.

Table 8 reports the effect of maternal non-employment on children's employment probability. Columns 2 to 4 report the results using the constructed instruments, and Column 1 shows the non-instrumented results for comparison. Notably, the instrumented coefficients on non-employment exposure are statistically significant when using the job's cyclical sensitivity as an instrument but not significant in the specification that uses only the durability measure. Again, all point estimates are in line. These results show that involuntary maternal non-employment driven by business cycles negatively impacts children's future employment prospects.

Table 7: 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)
OLF + UNEMP	-0.042^{+}	-0.260*	-0.220	-0.241*
	(0.026)	(0.150)	(0.196)	(0.146)
Permanent Income	0.119**	0.131**	0.134**	0.131**
	(0.026)	(0.028)	(0.030)	(0.028)
Inst. for Measurement Error	Yes	Yes	Yes	Yes
Cyclical-Job Measure		Yes		Yes
Durability Measure			Yes	Yes
F statistic	13.684	10.527	6.773	8.760
Observations	7,522	7,522	7,522	7,522
R2	0.268	0.249	0.253	0.252

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 6 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.

4.5 Inspecting the Mechanisms

In this section, we present other results that inform us of potential mechanisms that could explain the scarring effects of maternal unemployment. First, we show that these effects vary across the child's development stages. Exposure to maternal unemployment has a similar negative effect on wages, regardless of whether the child experienced it before or after age 12. Second, we look at different assessment tests available in the NLSY-CYA to document how maternal unemployment impacts children's development. Exposure to maternal unemployment harms children's home environment but does not seem to affect their cognitive development. Lastly, we use the ATUS to document that mothers allocate most of the extra time available after unemployment to leisure. The increase in activities related to children's education is minimal.

4.5.1 Different Impact at Different Stages of the Life cycle

We documented the effect of total exposure to maternal non-employment during the child's first 18 years. However, it could be that this effect varies across different stages of the child's development,

Table 8: Using Exposure to Cyclical Industries to Disentangle Voluntary and Involuntary OLF: Effects on Employment

	(1) emp.	(2) emp.	(3) emp.	(4) emp.
OLF + UNEMP	-0.122**	-0.195*	-0.156	-0.186*
	(0.019)	(0.107)	(0.137)	(0.105)
Permanent Income	0.027+	0.033*	0.033+	0.035*
	(0.017)	(0.018)	(0.021)	(0.018)
Inst. for Measurement Error	Yes	Yes	Yes	Yes
Cyclical-Job Measure		Yes		Yes
Durability Measure			Yes	Yes
F statistic	23.055	15.933	8.859	13.455
Observations	19,486	19,486	19,486	19,486
R2	0.091	0.089	0.090	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 6 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.

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.

Table 9, Column 2 shows our results. First, focusing on the coefficients on permanent income, we find a stronger estimated effect of early income relative to late income, consistent with the results of Caucutt and Lochner (2020). Second, the effects of exposure to maternal labor-force participation also differ across the two age periods. For children under 12, there is a statistically insignificant association, while for those over 12, the association is negative. This pattern may suggest that having a mother at home provides benefits (or is harmless) when the child is younger, but these benefits diminish as the child approaches adulthood. Lastly, exposure to maternal unemployment has a similar negative effect on wages, regardless of whether the child experienced it before or after age 12. The aggregate impact of maternal unemployment exposure seems to be divided equally between the two periods analyzed when comparing Columns 1 and 2.

Table 9, Column 4, shows the life-cycle results for employment probability. Interestingly, only the permanent income, the exposure to unemployment, and the exposure to labor-force non-participation that happened before age 12 have an impact on children's labor market outcomes. The impact of these variables measured after age 12 has the expected sign but also large standard deviations.

It is interesting that exposure to maternal unemployment harms children regardless of which stage of development we measure. We cannot pin down which mechanisms are behind these effects, but given the similarity of our results to the ones of Caucutt and Lochner (2020), we believe that credit constraints and complementarity between early and late investments in child development play an important role. Blau and Grossberg (1992) find that within the first four years of a child's life, the timing of maternal employment significantly influences children's cognitive development. So, a dataset with a larger sample size might allow looking at finer intervals of maternal unemployment, which can potentially reveal interesting heterogeneity.

Table 9: The Impact by Children's Life-cycle Stage

	Baseline	Life-Cycle	Baseline	Life-Cycle
	(1)	(2)	(3)	(4)
	log(wage)	log(wage)	emp.	emp.
OLF	-0.074**		-0.135**	
	(0.023)		(0.017)	
UNEMP	-0.296**		-0.243**	
	(0.076)		(0.068)	
Permanent Income	0.082**		0.024**	
	(0.009)		(0.007)	
OLF when child is bw 0-12		0.012		-0.112**
		(0.026)		(0.019)
OLF when child is bw 13-18		-0.084**		-0.019
		(0.024)		(0.018)
UNEMP when child is bw 0-12		-0.129*		-0.169**
		(0.072)		(0.062)
UNEMP when child is bw 13-18		-0.154**		-0.087
		(0.065)		(0.055)
PI when child is bw 0-12		0.057**		0.019**
		(0.010)		(0.007)
PI when child is bw 13-17		0.037**		0.003
		(0.009)		(0.006)
Educ Dummies	Yes	Yes	Yes	Yes
Observations	7,740	7,740	20,006	20,006
R2	0.258	0.262	0.087	0.087

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 (PI) is in $10,000s (discounted present value) as of birth year. See equation (2) for construction details. Columns 1 and 3 measure OLF, UNEMP, and PI when children are between the ages of 0 and 18. Columns 2 and 4 measure OLF, UNEMP, and PI for two periods: when children are between the ages of 0 and 12 and between 13 and 18. Baseline controls 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. 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.

4.5.2 The Impact on Home Environment and School Performance

Maternal unemployment might he causing the scarring effects because it harms children's development. For example, it is possible the stress that mothers face when losing a job and not finding a new one also stresses children, affecting their mental health, behavior, and development. In this subsection, we use two assessment tests available in 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 10, 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 child-care skills, dummy variables for children's race and gender, a cubic polynomial in children's age, and survey-year fixed effect.

In Column 1, we document a negative relationship between exposure to maternal unemployment and the overall home environment. This result suggests that unemployment indeed affects the quality of maternal care. In Columns 2 and 3, we document a negative relation between maternal unemployment exposure and the two subscores of the HOME measure, emotional support and cognitive stimulation scores. However, only the first is statistically significant. In Column 4, we document a negative but insignificant relation between exposure to maternal unemployment and the average PIAT score. In Column 5, we show that the relation between the MATH score and maternal unemployment is also statistically insignificant.[11] In sum, Columns 1 and 2 show that maternal unemployment negatively affects the child's home environment, while Columns 3-5 show that the cognitive development is not affected.

4.5.3 Amount of Time Investment by Mothers' Labor Market Status

Unemployment decreases family income but increases the amount of time a mother can spend at home with her children. Since we find that the overall impact of maternal unemployment is negative, it suggests that the increase in the available time does not compensate for lower family income. This in turn might be because it does not translate into productive time spent with the child.

[11] We get even smaller coefficients when we look at the effect of maternal unemployment on Math PIAT administered when the children are 10-12 years old.

Table 10: The Impact on Home Environment and Overall Development

	(1) HOME Total	(2) Emotional	(3) Cognitive	(4) Avg. PIAT	(5) Math PIAT
OLF 0-5	-0.152**	-0.095*	-0.140**	-0.044	-0.052
	(0.049)	(0.056)	(0.053)	(0.054)	(0.053)
UNEMP 0-5	-0.611**	-0.773**	-0.262	-0.100	0.117
	(0.192)	(0.209)	(0.206)	(0.182)	(0.189)
Permanent Income 0-5	0.156**	0.100**	0.166**	0.097**	0.078**
	(0.022)	(0.021)	(0.021)	(0.024)	(0.022)
Mom Educ Dummies	Yes	Yes	Yes	Yes	Yes
Mom AFQT	Yes	Yes	Yes	Yes	Yes
Observations	6,841	6,512	6,679	6,601	6,601
R2	0.314	0.208	0.260	0.189	0.183

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. 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.

Because children more exposed to maternal unemployment have worse labor force outcomes, the increased available time does not compensate for lower family income and likely implies that it does not translate into productive time spent with the child. To further investigate this hypothesis, we examine mothers' allocation of time. Since the NLSY does not have information on time use, we utilize the Annual American Time Use Survey (ATUS) data. The ATUS, conducted by the BLS, 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 11, we compare the time allocation of these women when they are employed, unemployed, and out of the labor force. When comparing employed and unemployed mothers, the most significant difference lies in the substantially less time the latter spends on work and work-related activities. An employed mother works, on average, 5 hours, 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 leisure by 1 hour and 21 minutes, other activities by 1 hour and 14 minutes, and, crucially, only 6 extra minutes are spent on activities related to children's education. Even though unemployed mothers increase the time allocated to children's education by 79.3% relative to employed mothers, the total amount of the increase is minimal.

Mothers out of the labor force spend more time with their children than those unemployed, a little more than half an hour. 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 being out of the labor are much lower than those of mothers being unemployed.

Table 11: Average Number of Minutes per Mother' Status

	Emp	Unemp	OLF
Total, all activities	1440.00	1440.00	1440.00
Caring for and helping household members	102.82	136.30	175.94
Caring for and helping household children	85.50	118.24	155.29
Activities related to household children education	8.11	14.54	17.72
Activities related to household children health	2.43	3.19	4.12
Caring for and helping household children (Other)	74.96	100.51	133.45
Personal care	553.12	589.59	579.83
Eat and drinking	65.50	65.27	70.74
Household activities	124.77	198.30	214.65
Purchasing goods and services	50.62	62.65	59.95
Caring for and helping non-household members	6.71	13.61	9.29
Working and work-related activities	296.40	26.87	4.02
Educational activities	6.73	18.39	13.73
Organizational, civic, and religious activities	16.75	22.61	23.52
Leisure and sports	196.70	278.10	259.35
Telephone calls, mail, and e-mail	6.87	10.36	10.09
Other activities not elsewhere classified	13.00	17.95	18.88

Note: The sample consists of women between 25 and 50 who reported having children under 18 living in the household. We have 29,414 employed, 2,036 unemployed, and 10,271 out-of-the-labor-force respondents. Time allocation categories are the major BLS aggregate categories. Each cell represents averages. We use sample weights.

In Appendix B, Tables B16 and B17 compare the time allocation of mothers given their labor market statuses and other characteristics. In Table B16, we compare employed and unemployed mothers whose families' total annual incomes are above $60,000 with those who have a family income below $60,000. Interestingly, poor-unemployed mothers increase their time allocated to children by 110% relative to poor-employed mothers, from 7.6 daily minutes to 15.9. On the other hand, rich-unemployed mothers only increase it by 27%, from 8.7 daily minutes to 11. Poor mothers seem to compensate more for the lower income with extra time invested in their kids when unemployed.

In Table B17, we compare the time allocation of employed, unemployed, and out-of-the-labor-force mothers across different education levels. We find that the time allocated to caring for children increases with education, irrespective of their employment status, confirming the findings of Guryan, Hurst, and Kearney (2008). This pattern is not as clear for the activities specifically related to children's education. Interestingly, while we found that the increase in time allocated to children's education when becoming unemployed depends on income, we do not find a similar relation with the education level. We speculate that these results speak to the presence of credit constraints that might be captured by looking across family income rather than by looking across education groups.

5 Conclusion

In this paper, we revisit whether exposure to maternal non-employment affects children's future labor market outcomes. The existing literature addresses this question by comparing displaced workers with non-displaced ones and finds that parental job loss harms children's future education attainment and wages. This approach, however, does not allow for the separation of the effect of income loss from other potential channels and does not account for how long the parent is unemployed during their children's childhood.

We use a different approach that isolates the income effect and accounts for different patterns of unemployment spells. In particular, we construct a measure of children's exposure to maternal unemployment as the fraction of their childhood spent with their mothers unemployed. We also create a similar measure for the exposure to a mother being out of the labor force, which allows us to compare the effects of different types of non-employment.

Constructing these measures 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 show this by contrasting the effects of having an unemployed mother and a mother who is out of the labor force and by using the exposure to cyclical industries as an instrument for involuntary labor-force non-participation.

To investigate potential mechanisms beyond income loss, we look at the correlation between maternal non-employment and home environment measures. The results suggest that maternal unemployment is detrimental to the quality of the home environment, although it does not significantly affect the child's cognitive test scores. We also use the ATUS survey and show that unemployed mothers do not spend extra time on their children's education compared to employed mothers.

Our research provides evidence that maternal unemployment has a significant and lasting negative impact on their child's future labor market outcomes. The scarring effects of unemployment extend beyond the immediate income loss. These findings highlight the importance of addressing maternal unemployment in order to reduce its costs for children properly.

References

Agostinelli, F. and G. Sorrenti (2022): "Money vs. Time: Family Income, Maternal Labor Supply, and Child Development," *Working Paper.*

Bastian, J. and L. Lochner (2020): "The EITC and maternal time use: more time working and less time with kids?" *Working Paper.*

Bils, M. and P. J. Klenow (1998): "Using consumer theory to test competing business cycles models," *Journal of Political Economy*, 106, 233–261.

Bils, M., P. J. Klenow, and B. A. Malin (2013): "Testing for Keynesian labor demand," *NBER Macroeconomics Annual*, 27, 311–349.

Blau, F. D. and A. J. Grossberg (1992): "Maternal Labor Supply and Children's Cognitive Development," *The Review of Economics and Statistics*, 74, 474–481.

Bonin, H., T. Dohmen, A. Falk, D. Huffman, and U. Sunde (2007): "Cross-sectional earnings risk and occupational sorting: The role of risk attitudes," *Labour Economics*, 14, 926–937.

Card, D. (1999): "The causal effect of education on earnings," *Handbook of Labor Economics*, 3, 1801–1863.

Carneiro, P. and J. Heckman (2003): "Human Capital Policy," *IZA Discussion Papers*, IZA DP 821.

Caucutt, E., L. Lochner, J. Mullins, and Y. Park (2023): "Child skill production: Accounting for parental and market-based time and goods investments," *Working Paper.*

Caucutt, E. M. and L. Lochner (2020): "Early and late human capital investments, borrowing constraints, and the family," *Journal of Political Economy*, 128, 1065–1147.

Coelli, M. B. (2011): "Parental job loss and the education enrollment of youth," *Labour Economics*, 18, 25–35.

Cunha, F., J. J. Heckman, and S. M. Schennach (2010): "The Intergenerational Effects of Worker Displacement," *Econometrica*, 78, 883–931.

Cygan-Rehm, K., D. Kuehnle, and M. Oberfichtner (2017): "Bounding the causal effect of unemployment on mental health: Nonparametric evidence from four countries," *Health Economics*, 26, 1844–1861.

Fradkin, A., F. Panier, and I. Tojerow (2019): "Blame the parents? How parental unemployment affects labor supply and job quality for young adults," *Journal of Labor Economics*, 37, 35–100.

Galassi, G., D. Koll, and L. Mayr (2021): "The Intergenerational Correlation of Employment: Mothers as Role Models," *Working Paper.*

Guryan, J., E. Hurst, and M. Kearney (2008): "Parental education and parental time with children," *Journal of Economic perspectives*, 22, 23–46.

Hartog, J. and W. P. Vijverberg (2007): "On compensation for risk aversion and skewness affection in wages," *Labour Economics*, 14, 938–956.

Hegarty, C. (2022): "Intergenerational Occupation Choice," *Working Paper*.

Hilger, N. G. (2016): "Parental job loss and children's long-term outcomes: Evidence from 7 million fathers' layoffs," *American Economic Journal: Applied Economics*, 8, 247–283.

Jacobson, L. S., R. J. LaLonde, and D. G. Sullivan (1993): "Earning Losses of Displaced Workers," *The American Economic Review*, 83, 685–709.

McLaughlin, K. J. and M. Bils (2001): "Interindustry mobility and the cyclical upgrading of labor," *Journal of Labor Economics*, 19, 94–135.

Necker, S. and A. Voskort (2014): "Intergenerational Transmission of Risk Attitudes–A revealed preference approach," *European Economic Review*, 65, 66–89.

Oreopoulos, P., M. Page, and A. H. Stevens (2008): "The Intergenerational Effects of Worker Displacement," *Journal of Labor Economics*, 26, 455–483.

Rege, M., K. Telle, and M. Votruba (2011): "Parental job loss and children's school performance," *The Review of Economic Studies*, 78, 1462–1489.

Stevens, A. H. (1997): "Persistent Effects of Job Displacement: The Importance of Multiple Job Losses," *Journal of Labor Economics*, 15, 165–188.

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: Descriptive Statistics

	Non-missing Emp Status	Non-missing Wage
Sample size	22,920	8,682
UNEMP	0.052	0.049
	(0.076)	(0.076)
OLF	0.354	0.328
	(0.295)	(0.275)
Permanent income	0.813	0.865
	(0.829)	(0.897)
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)
Education		
Less HS	0.34	0.27
High School	0.32	0.32
Some College	0.24	0.26
College or more	0.11	0.16
Mother's Education		
Less HS	0.17	0.14
High School	0.46	0.48
Some College	0.26	0.27
College or more	0.12	0.11

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 (4) 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.

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.

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 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.

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 three 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 or something; (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.

In Table B1, we perform 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
	(1)	(2)	(3)	(4)
	log(wage)	log(wage)	log(wage)	log(wage)
OLF	-0.122**	-0.099**	-0.094**	-0.109**
	(0.024)	(0.024)	(0.025)	(0.023)
UNEMP	-0.375**	-0.443**	-0.434**	-0.333**
	(0.076)	(0.079)	(0.085)	(0.074)
Permanent Income	0.105**	0.094**	0.111**	0.100**
	(0.010)	(0.009)	(0.010)	(0.009)
Observations	8,377	4,118	4,118	11,424
R2	0.192	0.187	0.187	0.192

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 Other Labor Market Outcomes: Earning Risk

In our analysis, we documented that exposure to maternal unemployment and labor-market non-participation predicts lower earnings for the children of the NLSY79. It is plausible to imagine that a child who is exposed to maternal unemployment self-selects into safer occupations, probably because the child might develop a risk aversion against earning or unemployment risk. Indeed, Hegarty (2022) finds evidence of the same 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 tested whether this channel is also present in our NLSY sample.

Following Bonin, Dohmen, Falk, Huffman, and Sunde (2007), Hartog and Vijverberg (2007), and Necker and Voskort (2014), we construct a measure of occupational earning risk using the residuals from Mincer equation regressions. First, we stack the March Current Population Survey (CPS) data from 1998 to 2021 and regress wages on a cubic polynomial in potential experience, educational attainment dummies, sex and race dummies, year-fixed effects, and occupation dummies. The occupation dummies capture the mean wage for each occupation. Second, we calculate the standard deviation of the residuals within each occupation to measure occupation risk. We only include occupations with at least 100 individuals in our sample. We normalize the measure by its standard deviation, allowing the regression coefficient to be interpreted as the impact of working in an occupation with one standard deviation above the average risk. We use the Autor-Dorn crosswalk to harmonize occupation codes across years.

Table B2, Column 1 shows that increases in unemployment exposure are associated with lower occupational earning risk. 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. Interestingly, we do not find any impact of our non-participation measure on occupational risk. In Column 2, we focus on individuals over 30 years old. The rationale behind this choice is that if the previous result is related to risk aversion, we expect older workers to exhibit a stronger effect (i.e., even lower occupational risk). Due to the time required for job search and career transitions, older workers have had more opportunities to self-select into occupations aligned with their risk preferences. Indeed, we find a more pronounced effect for this subgroup in Column 2.

In Columns 3 and 4, we examine the results by life cycle, breaking down the exposure to non-participation in the labor market into two childhood stages: ages 0 to 12 and 13 to 18. We find that exposure to non-participation has a negative impact on occupational earning risk during the first 12 years of childhood, but a positive impact during the later years. Exposure to unemployment negatively affects occupational earning risk only during the early childhood and has no significant effect during the later years. These findings suggest that experiences from 0 to 12 are particularly important in shaping risk preferences. In Column 4, we observe that the results are even stronger when we focus on older individuals with more than 30 years of potential experience.

Our baseline measure of occupational earning risk is constructed using 3-digit occupations. In Table

Table B2: Other Labor Market Outcomes: Earning Risk

	Baseline	More than 30 yrs.	Life Cycle	Life Cyle and +30 yrs.
	(1)	(2)	(3)	(4)
	Occ Risk	Occ Risk	Occ Risk	Occ Risk
OLF	0.061	-0.023		
	(0.056)	(0.086)		
UNEMP	-0.342*	-0.835**		
	(0.190)	(0.244)		
OLF when child is bw 0-12			-0.100	-0.187*
			(0.062)	(0.097)
OLF when child is bw 13-18			0.169**	0.167*
			(0.057)	(0.089)
UNEMP when child is bw 0-12			-0.310*	-0.793**
			(0.188)	(0.244)
UNEMP when child is bw 13-18			-0.005	0.023
			(0.153)	(0.222)
Permanent Income	0.115**	0.092**	0.111**	0.090**
	(0.024)	(0.040)	(0.024)	(0.040)
Observations	8,072	2,386	8,072	2,386
R2	0.029	0.042	0.031	0.045

Note: See text for details how how earning risk is constructed. 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, 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.

B3, we check the robustness of the results when constructing the risk measure using 2-digit occupations. In Columns 1 and 2, we observe that the impact of unemployment exposure is negative only when using 3-digit occupations, while the impact of non-participation exposure is close to zero for both measures. In Columns 3 and 4, the impact of non-participation exposure is close to zero when experienced between ages 0 and 12 but positive when experienced between ages 13 and 18. This result holds for both occupation measures. On the other hand, maternal unemployment experienced between ages 0 and 12 is negatively associated with occupational earning risk for both occupation measures. Interestingly, we find a zero effect of unemployment exposure during ages 13 and 18 when measuring risk using 3-digit occupations but a positive effect when measuring risk using 2-digit occupations. The reason for this difference in the impact of unemployment exposure during ages 13 and 18, depending on the level of occupation coarseness, is left for future research. When focusing on a sample of older adults (more than 30 years of potential experience), the magnitude of the results is larger, but the signs remain consistent.

Table B3: Other Labor Market Outcomes: Earning Risk

	Baseline		Life Cycle	
	(1)	(2)	(3)	(4)
	3D-Occ Risk	2D-Occ Risk	3D-Occ Risk	2D-Occ Risk
OLF	0.061	0.100*		
	(0.056)	(0.055)		
UNEMP	-0.342*	-0.043		
	(0.190)	(0.226)		
OLF when child is bw 0-12			-0.100	-0.049
			(0.062)	(0.062)
OLF when child is bw 13-18			0.169**	0.145**
			(0.057)	(0.054)
UNEMP when child is bw 0-12			-0.310*	-0.385*
			(0.188)	(0.201)
UNEMP when child is bw 13-18			-0.005	0.413**
			(0.153)	(0.187)
Permanent Income	0.115**	0.105**	0.111**	0.101**
	(0.024)	(0.022)	(0.024)	(0.022)
Educ Dummies	Yes	Yes	Yes	Yes
Mom Educ Dummies	Yes	Yes	Yes	Yes
Observations	8,072	8,297	8,072	8,297
R2	0.029	0.022	0.031	0.024

Note: See text for details how the earning risk is constructed. 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, 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.3 Non-Linear Effects on Wages and Employment Probabilities

Table 4 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. Since the exposure to labor-force non-participation is much more dispersed and has a much higher mean than unemployment, the bins are grouped differently. 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, on the other hand, are more linear.

For the child's employment outcome the effects are slightly different. In this case, exposure to unemployment for less than a year does not seem to have any effect on children's employment probability.

Table B4: Exploring Non-linearity in the Effects of Maternal Labor-Force Non-Participation

	(1) log(wage)	(2) log(wage)	(3) emp.	(4) emp.
olf: 4.5-9 years	-0.036**	-0.011	-0.068**	-0.060**
	(0.015)	(0.016)	(0.011)	(0.011)
olf: 9-13.5 years	-0.083**	-0.042**	-0.087**	-0.070**
	(0.018)	(0.018)	(0.013)	(0.013)
olf: > 13.5 years	-0.136**	-0.099**	-0.199**	-0.156**
	(0.020)	(0.024)	(0.014)	(0.017)
unemp: 3-12 months	-0.075**	-0.042**	-0.016	-0.013
	(0.015)	(0.015)	(0.011)	(0.011)
unemp: 1-3 years	-0.108**	-0.049**	-0.046**	-0.029**
	(0.017)	(0.018)	(0.012)	(0.013)
unemp: > 3 years	-0.155**	-0.092**	-0.093**	-0.069**
	(0.025)	(0.027)	(0.019)	(0.020)
Permanent Income		0.151**		0.047**
		(0.024)		(0.016)
F statistic		15.584		18.856
Observations	8,299	8,016	22,920	21,737
R2	0.166	0.186	0.067	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. 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.4 All Labor Market Outcomes

Throughout the paper we analyzed several labor market outcomes: (1) total earnings, (2) wages, (3) weekly hours, (4) employment probability, and (5) and occupation risk. However, in most of our analysis, we only focus on wages and employment probability. In Table B5, we present the results of Table 5, Column 5 to all outcomes.

Column 1 shows a statistically insignificant negative association between total earnings and unemployment exposure and a statistically significant negative association with non-participation exposure. Column 3 reveals a positive association between weekly hours and unemployment exposure and a negative association with non-participation exposure. Permanent income does not appear to impact hours. Column 5 examines occupational risk, finding no relation with non-participation exposure and a negative relation with unemployment exposure. Permanent income does not appear to impact occupational risk. The impacts on wage and employment probability were previously shown in Table 5, Column 5, and Table 6, Column 5, respectively.

Table B5: Robustness: All Labor Market Outcomes

	(1) log(total earn.)	(2) log(wage)	(3) log(hours)	(4) Employed	(5) Occ Risk
OLF	-0.144**	-0.029	-0.029**	-0.124**	0.070
	(0.046)	(0.026)	(0.012)	(0.019)	(0.071)
UNEMP	-0.164	-0.207**	0.089**	-0.125*	-0.517**
	(0.149)	(0.078)	(0.037)	(0.069)	(0.208)
Permanent Income	0.110**	0.120**	0.002	0.034*	0.048
	(0.047)	(0.025)	(0.014)	(0.018)	(0.065)
Educ Dummies	Yes	Yes	Yes	Yes	Yes
Mom Educ Dummies	Yes	Yes	Yes	Yes	Yes
Mom AFQT	Yes	Yes	Yes	Yes	Yes
Add. unemp	Yes	Yes	Yes	Yes	Yes
F statistic	12.710	12.710	12.710	14.634	12.407
Observations	7,708	7,708	7,708	20,102	7,495
R2	0.232	0.270	0.072	0.094	0.032

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 includes mothers' Armed Forces Qualification Test (AFQT) scores. We include the test scores as quantiles of the score distribution. Column 4 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.

B.5 Additional Controls

In Table B6, we add more controls to fully account for the childhood environment when growing up. Column 1 replicates the baseline result from Table 5, Column 5. 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 all of these additional controls simultaneously. Notably, after controlling for the full set of childhood environmental factors and the mother's unobserved ability, the estimated impact of maternal unemployment on adult wages actually increases in magnitude 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 B6: Robustness: Additional Controls

	Baseline	w/ Mom's Age	Mom's Spouse	Family Envir.	All Controls
	(1)	(2)	(3)	(4)	(5)
	log(wage)	log(wage)	log(wage)	log(wage)	log(wage)
OLF	-0.029	-0.027	-0.021	-0.031	-0.021
	(0.026)	(0.026)	(0.028)	(0.026)	(0.028)
UNEMP	-0.207**	-0.208**	-0.321**	-0.209**	-0.323**
	(0.078)	(0.078)	(0.087)	(0.078)	(0.087)
Permanent Income	0.120**	0.117**	0.121**	0.118**	0.117**
	(0.025)	(0.026)	(0.025)	(0.026)	(0.027)
Educ Dummies	Yes	Yes	Yes	Yes	Yes
Mom Educ Dummies	Yes	Yes	Yes	Yes	Yes
Mom AFQT	Yes	Yes	Yes	Yes	Yes
Add. unemp	Yes	Yes	Yes	Yes	Yes
Mom Cubic in Age		Yes			Yes
Mom' Spouse Labor Supply			Yes		Yes
Family Environment				Yes	Yes
F statistic	12.710	12.679	13.392	11.852	11.754
Observations	7,708	7,708	6,906	7,696	6,894
R2	0.270	0.271	0.265	0.273	0.270

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. See Tables 5 and 6 for the definition of mothers' ability control. 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.6 Placebo test

Besides controlling for proxies for mothers' unobservable heterogeneity (see Table 5), we also do a placebo test. In particular, we control, in Table B7, 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. The critical assumption in our analysis is that the mothers' labor-market statuses are driven by exogenous factors and not by an unobservable heterogeneity. A reassuring result that we find in Table B7 is that mothers' labor market statuses when children are already in adulthood or before they are born are not related to their wages. This would suggest that there is something specific in the fact that mothers cannot find work during their children's childhood, which hurts children's future prospects.

In Column 1, we again 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. The results of exposure to maternal labor-market non-participation are statistically insignificant in all specifications.

Table B7: Placebo test

	(1) log(wage)	(2) log(wage)	(3) log(wage)	(4) log(wage)
OLF when child is bw 0-18	-0.030	-0.021	0.032	0.040
	(0.026)	(0.027)	(0.032)	(0.033)
OLF when child is bw 25-30		-0.019		-0.011
		(0.018)		(0.023)
OLF when child is bw -5-0			-0.043	-0.045*
			(0.027)	(0.027)
UNEMP when child is bw 0-18	-0.223**	-0.211**	-0.219**	-0.207*
	(0.073)	(0.075)	(0.102)	(0.106)
UNEMP when child is bw 25-30		-0.028		-0.017
		(0.053)		(0.069)
UNEMP when child is bw -5-0			0.045	0.041
			(0.076)	(0.077)
Permanent Income	0.120**	0.120**	0.062**	0.061**
	(0.025)	(0.025)	(0.022)	(0.022)
Educ Dummies	Yes	Yes	Yes	Yes
Mom Educ Dummies	Yes	Yes	Yes	Yes
Mom Controls	Yes	Yes	Yes	Yes
F statistic	12.688	12.573	11.095	11.515
Observations	7,708	7,668	4,161	4,121
R2	0.270	0.270	0.292	0.292

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.

B.7 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 B8, Columns 1 to 3 present the OLS results, and Columns 4 and 5 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 B9 shows that the employment probability results follow a similar pattern.

Table B8: Fixed-Effect Results: Wages

	OLS			IV	
	(1)	(2)	(3)	(4)	(5)
	log(wage)	log(wage)	log(wage)	log(wage)	log(wage)
OLF	0.057	0.056	0.047	0.035	0.027
	(0.094)	(0.093)	(0.094)	(0.072)	(0.073)
UNEMP	0.274	0.282	0.309	0.416	0.414
	(0.285)	(0.290)	(0.294)	(0.269)	(0.273)
Permanent Income	-0.028	-0.010	-0.015	0.429	0.326
	(0.046)	(0.046)	(0.047)	(0.383)	(0.368)
Educ Dummies		Yes	Yes		Yes
Mom Controls			Yes	Yes	Yes
F statistic				7.102	7.153
Observations	8,675	8,299	8,282	7,715	7,344
R2	0.679	0.691	0.692	0.115	0.144

Note: OLF and UNEMP are our exposure measures to maternal non-participation and unemployment. 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 includes dummy variables for children's race, a cubic polynomial in children's age, and fixed effects for the survey year. Column 2 includes, in addition, educational attainment dummies. Column 3 includes, in addition, dummy variables for mothers' marital and primary earner statuses. These equations were estimated by ordinary least squares. Column 4 includes dummy variables for children's race, a cubic polynomial in children's age, fixed effects for the survey year, and dummy variables for mothers' marital and primary earner statuses. Column 5 includes, in addition, children's educational attainment 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.

Table B9: Fixed-Effect Results: Employment

	OLS			IV	
	(1)	(2)	(3)	(4)	(5)
	empl.	empl.	empl.	empl.	empl.
OLF	-0.035	-0.039	-0.041	-0.020	-0.020
	(0.065)	(0.065)	(0.065)	(0.051)	(0.051)
UNEMP	-0.190	-0.227	-0.226	0.094	0.047
	(0.174)	(0.173)	(0.173)	(0.176)	(0.177)
Permanent Income	-0.001	0.005	0.007	0.452**	0.431**
	(0.025)	(0.025)	(0.025)	(0.195)	(0.196)
Educ Dummies		Yes	Yes		Yes
Mom Controls			Yes	Yes	Yes
F statistic				36.421	33.745
Observations	22,896	21,950	21,845	21,451	20,565
R2	0.337	0.350	0.349	-0.010	0.003

Note: OLF and UNEMP are our exposure measures to maternal non-participation and unemployment. 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 includes dummy variables for children's race, a cubic polynomial in children's age, and fixed effects for the survey year. Column 2 includes, in addition, educational attainment dummies. Column 3 includes, in addition, dummy variables for mothers' marital and primary earner statuses. These equations were estimated by ordinary least squares. Column 4 includes dummy variables for children's race, a cubic polynomial in children's age, fixed effects for the survey year, and dummy variables for mothers' marital and primary earner statuses. Column 5 includes, in addition, children's educational attainment 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.8 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's 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 kid, 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 B10 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 that there is 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 kid. For example, being exposed to an out-of-the-labor-force mother significantly reduces employment probability for daughters but not for 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 working as well. 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 stressful home environment.

Table B10: Differences by Gender

	(1) log(wage)	(2) log(wage)	(3) emp.	(4) emp.
OLF	-0.029	-0.037	-0.124**	-0.049**
	(0.026)	(0.034)	(0.019)	(0.024)
UNEMP	-0.207**	-0.202*	-0.125*	-0.281**
	(0.078)	(0.110)	(0.069)	(0.096)
Permanent Income	0.120**	0.120**	0.034*	0.030*
	(0.025)	(0.025)	(0.018)	(0.018)
Female	-0.104**	-0.109**	-0.055**	-0.018
	(0.012)	(0.019)	(0.009)	(0.014)
Female # OLF		0.017		-0.153**
		(0.043)		(0.032)
Female # UNEMP		-0.008		0.287**
		(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	12.710	12.779	14.634	14.640
Observations	7,708	7,708	20,102	20,102
R2	0.270	0.270	0.094	0.097

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 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.9 Cyclical Industry Exposure: Alternative Specification

In Tables 7 and 8, we use exposure to cyclical industries as an instrument to decompose non-employment into its voluntary and involuntary components, which contrasts with the other tables in the paper in which we look at unemployment and non-participation separately. In Table B11, we divide the unemployment and non-participation exposure measures and instrument them with our measures of cyclical industries exposure. Columns 2 and 4 show the results, while Columns 1 and 3 reproduce previous results for comparison. We use annual real GDP growth as the measure of the cycle.

Column 2 shows that, after instrumenting, the coefficient on non-participation exposure is negative and statistically significant. We interpret the non-participation predicted by mothers working in more cyclical industries as involuntary. The negative result is consistent with the scarring effects that mothers not being able to find employment cause in their children. The coefficient on unemployment exposure is negative but statistically insignificant. However, the Kleibergen-Paap Wald F statistic is 4.4, indicating that the specification suffers from weak instruments. The F statistic for the first stage is particularly lower for the unemployment exposure measure, which might explain the big standard deviation. All results should be interpreted with caution.

Column 4 shows the results for employment probability. As before, the coefficient on non-participation exposure is negative and statistically significant. However, the coefficient on unemployment exposure is positive and statistically significant. The specification again suffers from weak instruments, with a Kleibergen-Paap Wald F statistic of 3.5. All results should be interpreted with caution.

Table B11: Cyclical Industry Exposure: Alternative Specification

	(1) log(wage)	(2) log(wage)	(3) emp.	(4) emp.
OLF	-0.028	-0.258*	-0.121**	-0.236*
	(0.027)	(0.154)	(0.020)	(0.125)
UNEMP	-0.213**	-0.031	-0.138*	1.035*
	(0.079)	(0.692)	(0.071)	(0.624)
Permanent Income	0.123**	0.127**	0.028*	0.017
	(0.025)	(0.032)	(0.017)	(0.025)
Inst. for Measurement Error	Yes	Yes	Yes	Yes
Cyclical-Job Measure		Yes		Yes
Durability Measure		Yes		Yes
F statistic	13.636	4.434	22.820	3.451
Observations	7,522	7,522	19,486	19,486
R2	0.267	0.250	0.091	0.056

Note: OLF and UNEMP are our exposure measures to maternal non-participation and unemployment. 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 6 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 and 4 all exposure measures 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 10% and 5% levels.

In Tables 7 and 8, we use annual real GDP growth as the measure of the cycle. We use annual NBER indicators as the cycle measure in Table B12. Column 2 uses the industry's employment-cyclical sensitivity, Column 3 uses the durability measure, and Column 4 uses both. As in the previous tables, the specifications in Columns 2 and 4 are statistically significant, with the latter falling marginally to be significant at the 10% level. Again, the durability measure recovers the same point estimate, but the F-statistic shows a weak-IV problem.

Table B12: Cyclical Industry Exposure: NBER Indicators

	(1) log(wage)	(2) log(wage)	(3) log(wage)	(4) log(wage)
OLF + UNEMP	-0.042^{+}	-0.267*	-0.181	-0.222^{+}
	(0.026)	(0.149)	(0.182)	(0.138)
Permanent Income	0.119**	0.131**	0.130**	0.129**
	(0.026)	(0.028)	(0.030)	(0.028)
Inst. for Measurement Error	Yes	Yes	Yes	Yes
Cyclical-Job Measure		Yes		Yes
Durability Measure			Yes	Yes
F statistic	13.684	10.527	7.394	9.291
Observations	7,522	7,522	7,522	7,522
R2	0.268	0.248	0.258	0.255

Note: OLF and UNEMP are our exposure measures to maternal non-participation and unemployment. 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 6 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 and 4 all exposure measures 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 10% and 5% levels.

We use the deviation of total employment of a cubic trend as the cycle measure in Table B13. Again, Column 2 uses the industry's employment-cyclical sensitivity, Column 3 uses the durability measure, and Column 4 uses both. With this measure of cycle, all estimates fall to be significant. Also, all instruments seem to suffer from a weak-IV problem, even though we recover point estimate that goes in the same direction.

Table B13: Cyclical Industry Exposure: Cyclical Total Employment

	(1)	(2)	(3)	(4)
	log(wage)	log(wage)	log(wage)	log(wage)
OLF + UNEMP	-0.042^{+}	-0.145	-0.136	-0.084
	(0.026)	(0.184)	(0.206)	(0.179)
Permanent Income	0.119**	0.123**	0.126**	0.119**
	(0.026)	(0.028)	(0.030)	(0.028)
Inst. for Measurement Error	Yes	Yes	Yes	Yes
Cyclical-Job Measure		Yes		Yes
Durability Measure			Yes	Yes
F statistic	13.684	9.506	7.077	7.896
Observations	7,522	7,522	7,522	7,522
R2	0.268	0.263	0.263	0.267

Note: OLF and UNEMP are our exposure measures to maternal non-participation and unemployment. 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 6 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 and 4 all exposure measures 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 10% and 5% levels.

In Tables 7 and 8, we repeat the exercise for employment probability. We use annual NBER indicators and the deviation of total employment of a cubic trend as the cycle measure. Column 2 uses the industry's employment-cyclical sensitivity, Column 3 uses the durability measure, and Column 4 uses both. With these measures of the cycle, all estimates fall to be significant (or are significant only at the 15% level). The results for employment probability are not as robust to changes in the measure of the business cycle as the ones for wages.

Table B14: Cyclical Industry Exposure: NBER Indicators

	(1)	(2)	(3)	(4)
	emp.	emp.	emp.	emp.
OLF + UNEMP	-0.122**	-0.126	-0.063	-0.077
	(0.019)	(0.102)	(0.123)	(0.096)
Permanent Income	0.027+	0.028+	0.026	0.028+
	(0.017)	(0.018)	(0.020)	(0.018)
Inst. for Measurement Error	Yes	Yes	Yes	Yes
Cyclical-Job Measure		Yes		Yes
Durability Measure			Yes	Yes
F statistic	23.055	16.686	9.717	14.603
Observations	19,486	19,486	19,486	19,486
R2	0.091	0.091	0.090	0.090

Note: OLF and UNEMP are our exposure measures to maternal non-participation and unemployment. 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 6 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 and 4 all exposure measures 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 10% and 5% levels.

Table B15: Cyclical Industry Exposure: Cyclical Total Employment

	(1) emp.	(2) emp.	(3) emp.	(4) emp.
OLF + UNEMP	-0.122**	-0.166+	-0.171	-0.161+
	(0.019)	(0.113)	(0.133)	(0.108)
Permanent Income	0.027+	0.031*	0.033+	0.032*
	(0.017)	(0.019)	(0.021)	(0.018)
Inst. for Measurement Error	Yes	Yes	Yes	Yes
Cyclical-Job Measure		Yes		Yes
Durability Measure			Yes	Yes
F statistic	23.055	14.875	9.191	12.618
Observations	19,486	19,486	19,486	19,486
R2	0.091	0.090	0.090	0.090

Note: OLF and UNEMP are our exposure measures to maternal non-participation and unemployment. 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 6 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 and 4 all exposure measures 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 10% and 5% levels.

B.10 Additional Results on Mothers' Time of Use

Tables B16 and B17 compare the time allocation of mothers given their labor market statuses and other characteristics. In Table B16, we compare employed and unemployed mothers whose families' total annual incomes are above $60,000 with those who have a family income below $60,000. Interestingly, relatively to poor-employed mothers, poor-unemployed mothers increase their time allocated to children allocation by 110%, from 7.6 daily minutes to 15.9. On the other hand, rich-unemployed mothers only increase it by 27%, from 8.7 daily minutes to 11. Poor mothers seem to compensate more for the lower income with extra time invested in their kids when unemployed.

Respondents are asked to choose the category that represents the total combined income during the past 12 months for all members of the householder's family. We create the table dividing the sample by their reported categories and do not adjust the nominal values.

In Table B17, we compare the time allocation of employed, unemployed, and out-of-the-labor-force mothers across different educational attainment groups. We find that the time allocated to caring for children increases with education, irrespective of their employment status, confirming the findings of Guryan et al. (2008). Interestingly, this pattern is not so clear for activities specifically related to children's education. Also interestingly, our finding that, when unemployed, poor mothers increase the time allocated to children's education by more than rich mothers does not seem to be present across education groups. We speculate that these results speak to the presence of credit constraints that might be captured by looking across family income rather than by looking across education groups.

Table B16: Average Number of Minutes per Mother' Status and Family Income

	Less $60,000			More $60,000		
	Emp	Unemp	OLF	Emp	Unemp	OLF
Total, all activities	1440.00	1440.00	1440.00	1440.00	1440.00	1440.00
Caring for and helping household members	91.69	131.39	162.72	112.48	148.64	196.99
Caring for and helping household children	74.57	114.54	143.73	94.93	128.52	173.52
Activities related to household children education	7.57	15.90	16.53	8.65	10.98	19.74
Activities related to household children health	2.51	2.28	4.55	2.35	5.19	3.53
Caring for and helping household children (Other)	64.49	96.35	122.64	83.92	112.36	150.25
Personal care	563.25	598.94	594.86	545.72	565.99	557.41
Eat and drinking	60.10	62.03	65.29	69.72	74.98	79.32
Household activities	127.39	197.70	219.53	122.22	203.17	206.44
Purchasing goods and services	48.23	57.51	53.14	52.22	75.85	70.01
Caring for and helping non-household members	7.55	15.96	9.62	5.95	8.66	8.69
Working and work-related activities	296.48	27.31	4.11	296.05	26.65	3.93
Educational activities	8.41	21.85	14.27	5.27	9.83	12.61
Organizational, civic, and religious activities	16.05	18.82	20.46	17.30	32.69	27.53
Leisure and sports	201.82	282.63	270.77	192.50	260.42	241.90
Telephone calls, mail, and e-mail	6.62	8.89	7.71	6.97	12.28	13.57
Other activities not elsewhere classified	12.41	16.97	17.53	13.59	20.83	21.60

Note: The sample consists of women between 25 and 50 who reported having children under 18 living in the household. We have 29,414 employed (12,816 in group 1, 15,073 in group 2), 2,036 unemployed (5,607 in group 1, 478 in group 2), and 10,271 out-of-the-labor-force respondents (5,607 in group 1, 4,132 in group 2). Time allocation categories are the major BLS aggregate categories. Each cell represents averages. We use sample weights.

Table B17: Average Number of Minutes per Mother' Status and School Groups

	Less High School			High School			Some College			College More		
	Emp	Unemp	OLF	Emp	Unemp	OLF	Emp	Unemp	OLF	Emp	Unemp	OLF
Total, all activities	1440.00	1440.00	1440.00	1440.00	1440.00	1440.00	1440.00	1440.00	1440.00	1440.00	1440.00	1440.00
Caring for and helping household members	69.51	121.78	143.69	86.84	127.19	160.53	94.44	136.16	173.91	122.52	168.88	213.67
Caring for and helping household children	53.54	102.59	123.85	70.74	110.79	140.43	77.38	117.61	155.85	104.14	149.76	189.92
Activities related to household children education	7.54	12.90	12.64	7.76	13.99	19.69	7.63	17.04	19.53	8.71	13.58	17.80
Activities related to household children health	2.03	1.38	4.33	2.08	3.02	3.41	2.75	2.22	4.58	2.48	6.93	4.28
Caring for and helping household children (Other)	43.98	88.30	106.88	60.90	93.78	117.33	67.00	98.35	131.74	92.95	129.25	167.83
Personal care	582.97	597.20	607.00	562.04	610.96	591.37	554.83	582.99	575.27	542.29	552.55	554.32
Eat and drinking	59.20	62.30	65.35	59.85	55.54	62.76	62.97	66.87	68.82	71.31	83.71	83.44
Household activities	152.43	242.33	244.48	130.54	190.43	223.33	122.66	183.29	200.47	118.56	186.96	197.58
Purchasing goods and services	45.40	60.80	50.53	47.46	56.21	53.55	52.48	61.01	65.20	51.95	78.81	68.25
Caring for and helping non-household members	6.86	10.20	6.56	7.93	20.34	10.89	8.08	10.68	12.29	5.12	9.59	7.24
Working and work-related activities	293.00	14.78	5.74	297.96	28.46	2.98	297.57	32.48	3.04	295.32	28.76	4.63
Educational activities	2.90	4.94	5.80	4.18	11.18	11.05	10.55	36.21	24.88	6.20	19.32	12.86
Organizational, civic, and religious activities	13.53	17.97	17.97	15.12	20.06	20.24	16.36	23.78	22.95	18.42	30.53	30.80
Leisure and sports	196.78	280.49	274.01	210.29	297.08	275.27	200.30	278.09	262.17	186.83	241.19	232.23
Telephone calls, mail, and e-mail	3.87	6.57	4.67	5.97	7.13	9.03	7.03	12.52	10.11	7.75	17.08	14.69
Other activities not elsewhere classified	13.56	20.63	14.21	11.82	15.43	19.00	12.74	15.91	20.89	13.74	22.63	20.30

The sample consists of women between 25 and 50 who reported having children under 18 living in the household. We have 29,414 employed (1,536 in group 1, 5,875 in group 2, 8,917 in group 3, 13,086 in group 4), 2,036 unemployed (361 in group 1, 584 in group 2, 637 in group 3, 454 in group 4), and 10,271 out-of-the-labor-force respondents (1,553 in group 1, 2,519 in group 2, 2,703 in group 3, 3,496 in group 4). Time allocation categories are the major BLS aggregate categories. Each cell represents averages. We use sample weights.

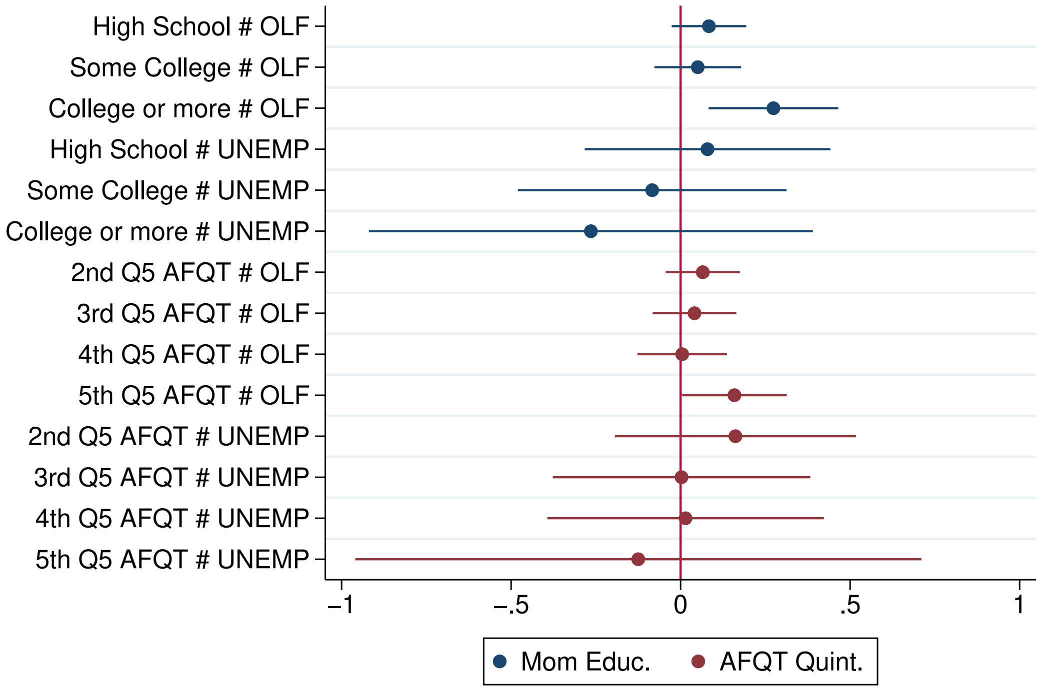
C Additional Figures

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. However, the results look different 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.