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ABSTRACT

Labor Demand Shocks at Birth and Cognitive Achievement during Childhood

As epidemiological studies have shown that conditions during gestation and early childhood affect adult health outcomes, we examine the effect of local labor market conditions in the year of birth on cognitive development in childhood. To address the endogeneity of labor market conditions, we construct gender-specific predicted employment growth rates at the state level by interacting an industry's share in a state's employment with the industry's national growth rate. We find that an increase in employment opportunities for men leads to an improvement in children's cognitive achievement as measured by reading and math test scores. Additionally, our estimates show a positive and significant effect of male-specific employment growth on children's Peabody Picture Vocabulary Test scores and in home environment in the year of birth. We find an insignificant positive effect of buoyancy in females' employment opportunities on said test scores.

JEL Classification: J20, J21, I20, I30

Keywords: labor market conditions, cognitive ability, child's well-being

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I. Introduction

The early months of a newborn's life are considered to have a profound and persistent role in formulating children's cognitive skills.[1] For example, early months largely determine the formation of synapses that permit communication between neurons, and the human brain reaches 50 percent of its mature weight by six months of age (see Woodhead 2006 for an extensive review). Having been born in periods of labor market buoyancy may help children's chances of having sufficient nutrient intake and a better living environment. Parents that can afford to purchase toys, musical instruments, and other educational materials may help stimulate children's cognitive ability. However, when the labor market is in a downturn, parents may have decreasing income levels, increasing mental stress, a deteriorating health condition, and a worsening home environment. This might deprive children from getting not only adequate nutrition, but also parental attention and emotional support, thus creating negative consequences for the child's development. At the same time, higher unemployment, which is associated with a decrease in labor supply, might yield more available time for parents, traditionally mothers, to engage in home production and take better care of the child. Given the importance of early life in laying the foundation for children's human capital accumulation and long-term prospects,[2] this paper investigates the link between labor market conditions at birth and cognitive achievement during childhood.

The crucial empirical problem of analyzing the effect of parents' labor market conditions at birth on outcomes later in life is that unobserved heterogeneity could jointly affect parental labor-market activity and children's educational attainment. Those parents who are more likely to be unemployed or lose jobs might have socioeconomic and home environments that are detrimental to children's progress. One potential approach to address this

[1]E.g., UNICEF 2014, Woodhead 2006, Conti and Heckman 2012.

[2]Epidemiologic studies provide further insight into why conditions during gestation affect adult health outcomes. Heijmans et al. 2008 show that periconceptional exposure to famine creates persistent epigenetic differences that can last up to six decades after birth. Likewise, Denney and Quinn (2018) and Ravlić et al. (2018) find that adverse maternal factors at the time of fetal growth increase a child's risk of developing chronic diseases in adulthood, including diabetes and obesity.

concern is to use a measure of labor market outcomes constructed at the macro level, such as the unemployment rate (van den Berg, Lindeboom and Portrait 2006). However, the main concern with the unemployment rate is that it is affected by both labor demand and supply, and differences in parents' labor supply behavior is related to differences in unemployment rates and in children's educational outcomes. Welfare programs in the U.S. that are normally expanded during periods of high unemployment are criticized for distorting work incentives and labor supply, resulting in a rise in the unemployment rate. For instance, Barro (2010) and Hagedorn, Manovskii and Mitman (2015) argue that the unemployment rate after the great recession of 2008-09 was artificially high because individuals were not returning to work due to a generous expansion of unemployment benefits. Likewise, the unemployment rate differs across race, ethnicity, and educational levels. The concentration of a particular racial or an (un)educated group in a particular state affects the state's unemployment rate. Differences in children's cognitive achievement associated with the unemployment rate could be the result of the composition of the unemployed.

To address potential confounders, this paper constructs predicted labor demand growth, which is arguably exogenous at the individual level. To do so, we calculate the share of each industry in a state's employment in the base year and interact it with the growth rate of the corresponding industry at the national level. We construct separate predicted growth rates for men and women to examine if improved employment opportunities for men and women have differential effects. Our empirical strategy is based on Bartik's (1991) "shift-share" approach,[3] which has been applied by Katz and Murphy (1992), Page, Schaller and Simon (2017), Aizer (2010), and Allcott and Keniston (2017), among others, in different contexts. Our analysis uses children from the National Longitudinal Survey

[3]Goldsmith-Pinkham, Sorkin and Swift (2018) provide a detailed review of the approach. Our identifying assumption is that industry shares in the base period are orthogonal to unobserved factors that affect children's cognitive development process decades later. This assumption is not subject to the criticism in Goldsmith-Pinkham, Sorkin and Swift (2018) as it is hard to argue that industry shares in the base year 1970 are correlated with educational outcomes in the late 1980s and the 1990s. We also analyze sensitivity of our findings in a robustness check by controlling for industry shares.

of Youth 1979 (NLSY79) Child and Young Adult that follows biological mothers in the NLSY79. The survey is conducted every other year (from 1986 to 2014) and has a rich set of information including widely used measures of cognitive ability such as math and reading scores and family background. We use children born between 1978 and 2009, who were 5 to 14 years of age, a group whose math and reading scores are available in our data.

We begin by assessing the way predicted gender-specific employment growths interact with parents' labor market outcomes in the year of birth. We find that predicted male-employment growth has a positive and significant effect on fathers' labor supply and earnings in the year of child birth. Furthermore, our estimates show that a one-percentage point rise in male-specific labor demand growth reduces the likelihood of the family being in poverty by around 1.4 percentage points. Our results show that predicted female-specific employment growth positively and significantly affects the number of weeks mothers worked in the year of child birth. However, the effect for mothers' wages is not statistically different from zero. It is worth noting that about a third of the women reported having zero weeks of employment in the year of child birth in our sample, suggesting that those mothers may be more focused on birth and other child related issues. In another set of results, we find that predicted employment growths are highly correlated with unemployment rates.

We next estimate the effects of gender-specific employment growths on children's test scores. We find that a one-percentage point rise in male-specific labor demand growth leads to a 0.018-0.033 standard deviation rise in math scores and a 0.025-0.032 standard deviation increase in reading scores. Our estimates show the positive effect of female-specific predicted labor demand growth, with the estimates showing increases of around 0.015 and 0.019 standard deviations in math and reading scores, respectively. That being said, we cannot statistically distinguish these estimates from zero. The differential effects across gender highlight the roles of both income and substitutability of parental care, as predicted by Becker and Tomes (1986). This is also in line with the existing theoretical ambiguity about whether a mother's employment should create positive or negative effects on children's cognitive ability. To the extent that mother's employment reduces the quality of care, children's cognitive development might be adversely affected. On the other hand, mother's employment and subsequent increase in family income lead to a positive effect on children's cognitive ability (e.g, Dahl and Lochner 2012). Rege, Telle and Votruba (2011), who investigate the micro effect of parental job loss that occurred when a child was in seventh grade on short-term educational performance, provides support to this ambiguity. The authors find an insignificant effect for mothers' job loss on a child's educational performance, but a significant and negative effect for fathers' job loss.

We assess the robustness of our findings to several specifications. We separately estimate the effect of male-specific predicted employment growth on the child's cognitive achievement by the marital status of their mothers in the year of birth. We find stronger effects on children of married mothers and insignificant effects on children of unmarried mothers. If mothers were unmarried at the child's birth, any improvement in men's employment opportunities may not affect them. These findings could be viewed as a falsification test. Even when we estimate the effect for male-specific employment growth, controlling for female-specific employment growth to account for any other effect on child achievement arising from interdependencies in spousal labor supply, the results are consistent. We also separately estimate the effect by race. This subgroup analysis shows that effects are more pronounced among white children. Moreover, as suggested by Jaeger, Ruist and Stuhler (2018), we control for the lagged value of predicted male-specific growth to account for the possibility of its serial correlation over time.

We extend our analysis to estimate the effect on the Peabody Picture Vocabulary Test (PPVT), which measures receptive vocabulary.[4] Our findings are similar to that of the reading and math scores. We find a significantly positive effective of male-specific predicted

[4]Although the primary focus of this paper is to study the effect on a child's cognitive development, we were curious about any effects on children's behavioral problems. We attempted to examine the effects on such problems, but found insignificant effects.

employment growth, but an insignificant effect of female-specific growth. In an attempt to further understand the mechanism behind the positive effect of labor market growth at birth in childhood, we investigate how labor market outcomes affect home environment in the year of birth. The NLSY has information about the quality of home environment. We find a significant and positive effect of male-specific predicted employment growth.

Finally, we explore a potential concern of whether couples self-select with regards to choosing a time for childbearing. If the self-selection–as shown by Dehejia and Lleras-Muney (2004)–occurs, our baseline model underestimates the effect of predicted employment growths. Dehejia and Lleras-Muney (2004) argue that low-income parents' skills deteriorate relatively faster, and thus the opportunity cost of having a child for a low-income family in labor market buoyancy is higher than that of a period of labor market slack. Likewise, low-earning couples might find periods of labor market booms more preferable as they may have enough financial resources to take care of the child. High-earning couples choose times of labor market slack to raise a child as their opportunity cost of childbearing becomes lower. We examine if predicted male-specific employment growth affects the behaviour of highly educated and less educated married mothers differently when it comes to having a baby. We do not find significant effects. Furthermore, we re-estimate our main findings using mother fixed effects. Our objective is to compare differences in outcomes of siblings due to differences in employment growth. Doing this allows us to net out time-invariant differences in family background. Our main results are consistent.

In examining the link between labor market conditions at birth and outcomes later in childhood, we contribute to three strands of the literature. First, this paper contributes to a small body of literature that examines the effect of the business cycle during childhood on later outcomes.[5] For example, van den Berg, Lindeboom and Portrait (2006) study the effect of the business cycle early in life on the individual mortality rate in adulthood. Using

[5] A number of research papers have studied the effects of shocks to pregnant mothers on child's health outcomes (e.g., Black, Devereux and Salvanes 2016).

birth cohorts from 1908 to 1937 in the Netherlands, van den Berg et al. (2010) examine how cognitive functioning in old age is affected by the business cycle in early life. Doblhammer, van den Berg and Fritze (2013) employ a cross-national survey consisting of respondents from 10 European countries to study the link between economic conditions at birth and cognitive functioning among the elderly. Ruhm (2004) shows that mother's employment in the first three years of a child's life leads to lower test scores at ages 5 to 6. Dehejia and Lleras-Muney (2004) examine the association between the unemployment rate during pregnancy and newborns' health. However, there is little evidence on the effect of labor market shocks in the year of a child's birth on educational outcomes. Rao's (2016) analysis is centered around examining how average unemployment rates experienced in the years between conception and age 15 are associated with outcomes in adulthood.

Second, our paper complements the existing literature that studies the role of job displacement on children's education (e.g, Hilger 2016, Stevens 1997, Pan and Ost 2014). Much of the literature attempting to investigate the impact of labor market conditions focuses on individual layoffs, in an attempt to circumvent an endogeneity problem. These findings represent the micro effect. We contribute to this literature by leveraging (an arguably exogenous) employment growth to capture the general equilibrium or full effect of unemployment.

Third, by examining the impact of female labor market conditions at birth, we contribute to the literature that examines the link between mother's employment and her child's educational outcomes. The literature does not reach a consensus with regards to the effect of maternal participation in the workforce on children's educational performance. James-Burdumy (2005) finds that maternal employment in the year after birth has a limited effect on a child's test scores. Blau and Grossberg (1992) show that children whose mothers work all weeks in the child's first year of life have lower test scores. Baum (2003) finds negative effects of maternal employment in the first year of a child's life on cognitive development.

Likewise, others find no significant effect of maternal employment (e.g., Kalil and Ziol-Guest 2008). These differential findings in the literature could be the result of selection bias (see Waldfogel 2002 and Bernal 2008), which we attempt to address.

The remainder of the paper unfolds as follows: Section II builds a conceputal framework to show potential channels between labor market conditions at birth and educational outcomes during childhood. Section III describes our data and Section IV our empirical specification. We present results in Section V and apply a mother fixed effects model in Section VI. Section VII concludes.

II. Conceptual Framework

We draw on Becker (1981) to illustrate how labor market conditions in the year of birth impact the child's cognitive production function, thus motivating the empirical exercise below. In Becker's model,[6] a household maximizes its utility by consuming a bundle of goods that includes a child as one component. The production of these goods requires inputs from the household members in the form of time and effort as well as market-based goods. As the value of household utility increases with a rise in the child's quality, household members focus on child care. However, the ability of household members or parents to improve the well-being or the quality of the child is tied with family endowments and their labor market opportunities. While total human capital up to a particular age is a dynamic, multistage, and complex phenomena, a child's early months, including the prenatal period, are crucial in a child's brain development (Woodhead 2006). The production of synapses that permits communication between neurons peaks in the first year of life (Tierney and Nelson 2009).

To show how the formation of the child's cognitive development is potentially shaped by early life circumstances associated with parents' labor market outcomes, we explain the

[6]Given the sample time period, this model is analogously appropriate.

link between three major inputs (parental time, market-based goods, and child care) of the cognitive achievement production function and parental labor market outcomes in the year of birth. To elucidate the role of parental time in a child's achievement, consider an example that the achievement of a 10-year-old child in the current year is influenced by time spent by parents on various activities with the child since birth, which include helping with homework, going on outings, and other physical and mental exercises. Likewise, note that market-based goods purchased over time include health expenditures, housing, and educational resources.

Given the importance of these three inputs in child development, parents face competing decisions: the tradeoff between engaging in home production and child care versus participating in the labor market to increase the affordability of marked-based goods. Additionally, the tradeoff gives insight into how fathers' and mothers' job market opportunities differ in fostering the child's development, as women have traditionally played the leading role when it comes to raising children. The psychology literature postulates that the major channel through which job loss affects children's cognitive development is through mental stress and breakdown in emotional connection between the father and child (Elder, Nguyen and Caspi 1985 and Christoffersen 2000). Better labor market conditions for fathers might help strengthen that emotional connection. With the rise in father's income associated with employment growth, the family could provide nourishment and better living conditions to the child. Similarly, an improvement in male job market conditions might help mothers reduce their labor market production and increase their home production (Bertrand, Kamenica and Pan 2015).

There are two major pathways through which improvement in maternal employment opportunities affect child development. Employment growth creates income and substitution effects with regard to the consumption of child care (Bernal and Keane 2011 and Ozabaci, Henderson and Su 2014), assuming that the child is a normal good. A rise in own-wage increases the relative price of home production and investment in the child. The decline in homemade goods, such as meals and child care could be detrimental to the child's psychology and in the formation of cognitive ability. However, higher income enables better diets, better access to health care, less stress, and goods that could stimulate a child's brain. If the reduction in home-goods is fully compensated by market goods, female-specific employment growth may have no effect, as positive and negative effects offset each other.

In summary, we argue that labor market outcomes in the year of birth have profound and persistent effects throughout childhood. Male-specific employment growth leads to a positive impact on the formation of a child's ability. On the other hand, since traditionally mothers play a key role in raising children, the effect of female-specific employment growth has an ambiguous effect. In the next section, we outline our empirical specification to estimate the effects of predicted employment growths on child achievement, leveraging plausibly exogenous variation in the local labor market.

III. Data

We use data from the National Longitudinal Survey of Youth (NLSY79) and the NLSY79 Child and Young Adult. The NLSY79 is a nationally representative longitudinal survey of 12,686 young individuals (6,403 males and 6,283 females) born between 1957 and 1964. In the first interview year 1979, respondents were 14-22 years old. The survey interviewed individuals every year from 1979 through 1994 and every other year thereafter. The latest available interview occurred in 2014. The data contain a rich set of information about educational background, labor market outcomes, and ability as measured by the Armed Forces Qualification Test (AFQT).

The NLSY79 Child and Young Adult cohort that was introduced in 1986 includes biological children of women in the NLSY79. The survey is conducted every two years and is ongoing. As of 2014, the latest survey, 11,521 children were born to women in the NLSY79.

Children appear in multiple surveys. Over 10,000 children appear in at least one survey. We can link these children to their mothers in the NLSY79. These datasets are suitable for the purpose of our study to examine the effect of local demand shocks at birth on educational outcomes later in life. The data allow us to trace the birth state of the child and include widely used measures of children's cognitive achievements.

We present a histogram with an overlaid kernel density plot of birth cohorts in Figure 1.[7] Most births occurred in the 1980s and 1990s. As our goal is to investigate the effect of labor market shocks at birth, we need to identify the birth state of children. As mothers have been interviewed since 1979, we could pinpoint the birthplace of only those children who were born in or after 1979. Hence, we exclude children who were born before 1979, which is about six percent of the total sample.

We use the restricted version of the data, as the publicly available version does not have geocode information. The NLSY79 includes a nationally representative cross-sectional sample along with an over-sample of Hispanic, black, economically disadvantaged whites, and members of the military. In our analysis, we exclude the over-sampled children, basing our analysis only on the cross-sectional sample. Furthermore, we use survey weights to make our sample representative of the population.

Outcome Variable: Math and Reading Scores

We use the Peabody Individual Achievement Test (PIAT) that assesses academic achievement of children. It has been widely used as a measure of cognitive ability. The test is administered every other year beginning with 1986. It is an age-appropriate test with an increase in difficulty level from preschool to high school. The tests are assessed to children 5 to 14 years of age. The PIAT includes tests in math and reading. The PIAT Math assesses a child's mathematics achievement. The PIAT Reading Recognition measures a child's word recognition and pronunciation ability. Both tests contain 84 items. We normalized these

[7]The kernel density estimate is obtained via the Wang and van Ryzin (1981) kernel function for ordered discrete data with a plug-in bandwidth (see Chu, Henderson and Parmeter 2015).

scores (mean zero, standard deviation one) for our analysis.

Outcome Variable: Peabody Picture Vocabulary Test

The Peabody Picture Vocabulary Test (PPVT) "measures an individual's receptive (hearing) vocabulary for Standard American English and provides, at the same time, a quick estimate of verbal ability or scholastic aptitude" (Dunn and Dunn 1981). The test has been designed targeting children as young as two and a half years to 40-year-old adults. In the NLSY79 Child and Young Adult survey, children 4-5 and 10-11 years of age took the PPVT. Additionally, the test was administered to some children falling in other age groups. The test includes 175 stimulus words along with 4 black-and-white drawings for each stimulus word for which the goal is to choose the drawing that best represents the meaning of the stimulus word. In our analysis, we normalize the total score.

Outcome Variable: Home Environment

The NLSY79 Child and Young Adult survey includes the Home Observation Measurement of the Environment-Short Form (HOME-SF) that is intended to assess the child's home environment. The HOME-SF includes a number of assessment items, which respondents are asked to report. These items are considered to be an input in child development. For example, the questionnaire items include indicators for whether the "Child gets out of house 4 times a week or more," "Child has 3 children's books," and "Child has one or more cuddly, soft or role-playing toys." Based on responses to these questions, the total raw score for the HOME-SF is calculated. In addition to the total raw score, the NLSY79 Child and Young Adult includes cognitive stimulation and emotional support scores based on these assessment items. This paper uses all three measures - total raw score, stimulation support score, and emotional support score. We normalize these scores and restrict our analysis to children aged 0 to 12 months, as our aim is to assess how labor market outcomes impact the children's home environment during the year of birth.

After matching children to mothers, we construct variables related to mothers. From

1979 to 1994, mothers' labor market outcomes and state of residence are available annually. Thereafter, they are available every other year. We use the average of the subsequent year and preceding year for each missing year to calculate income and other labor market variables. Likewise, to identify the state in each missing year, we use information from the subsequent year. For example, when a mother is not interviewed in 1995, we use her location in 1996 for the year 1995. In cases where the geocode information is missing in the next year, we use it from the previous year. Likewise, if mother's education information is missing in some surveys, we construct the education variable as the highest education achieved up to the point of the survey, using the current and previous surveys.

We merge these data with the unemployment rate data extracted from the Bureau of Labor Statistics. Likewise, we use the March Current Population Survey (CPS) each year from 1977 to 2010 and the 1970 U.S. decennial census to create the predicted employment growth rate as described in the next section. Descriptive analysis is provided in Table 1.

IV. Empirical Strategy

Our empirical analysis exploits variation in labor market shocks at birth over space and time and individual data to measure effects on children's educational outcomes. We pool data in a cross-sectional format. Our unit of analysis is a child-year, that is, we have observations for the same child in different years.[8] As parents' individual labor market outcomes in the year of birth could be correlated with children's cognitive development later in life, our approach here is to find a measure of labor market outcome that is exogenous at the individual level. For example, children, whose parents are unemployed, underemployed or out of the labor force, may have other adverse family and socioeconomic backgrounds that could negatively affect their educational achievements. To avoid our analysis being diluted by unobserved

[8] We also consider a child as a unit of analysis in robustness checks in Appendix (Table B1). We collapse test scores at the child level. In an alternative specification, we also limit our analysis to a child's first test score.

individual heterogeneity, we focus on macroeconomic variables. One approach to estimate the effect of labor market conditions at birth on educational outcomes later in life is to use the following equation:

$$A_i = \alpha + \beta_1 U_{st} + \lambda X_i + \rho Z_i + \gamma_t + \varsigma_b + \psi_s + B_l + \epsilon_i, \tag{1}$$

where i indexes a child-year and A represents a math or reading score. Although a child can appear repeatedly in our data, the variable of interest U_{st}, the state-level unemployment rate in the year of a child's birth t, does not vary by child. We use our data in a cross-sectional format. X includes a vector of children's characteristics which includes age, age-squared, and race. Z is a vector of mother characteristics which capture family backgrounds affecting child development. It includes mother's age, education, and AFQT scores[9] (the latter administered in 1980). We control for the number of siblings, as having many siblings divides parents' resources.[10] These variables are measured in each survey year. We include the mother's average permanent income, which is calculated as the average of mother's reported real wages[11] each year up to the point of the survey year.[12] γ_t are year-fixed effects, which are intended to capture shocks that are common to all states. For example, this could be any expansion or contraction in a federal welfare program or federal educational policy that equally affects all states. ς_b is a vector of state-of-birth fixed effects. This controls for state-specific differences such as education and health care during the year of birth. ψ_s represents a vector of state-of-residence fixed effects, which account for the time-invariant state-specific differences. Buckles and Hungerman (2013) show that season of birth is associated with outcomes in adulthood; to control for potential seasonality, we use the month-of-birth fixed

[9] We rescale the scores (dividing by 10,000) for simplicity of interpretation.

[10] It could be argued that sibling size is affected by prior labor market conditions and is endogenous. We re-estimate our model excluding it and our main results do not change.

[11] We use the Consumer Price Index for All Urban Consumers (CPI-U) to convert wages into real values. We use 1990 as the base year. We rescale wages (dividing by 10,000).

[12] We use this measure instead of mother's wage during the year of birth as wages in the year of birth could be noisy due to a mother's irregular participation in the labor market due to issues related to childbirth. Further, when we re-estimate our model excluding it, the main results do not change.

effects B_l. The error term (ϵ_i) contains unobserved factors that vary by child-year. α, β_1, λ, ρ, γ, ς, ψ and B are parameters to be estimated, where β_1 is the parameter of interest. We cluster standard errors at the state-of-birth level. We use survey weights to make our sample representative of the population.

Our measure of the unemployment rate at the state level could be problematic as it is affected by both labor demand and supply. For example, the unemployment rate at a particular time could be high if there is an increase in labor force participation. Another drawback of the unemployment rate is that it does not include discouraged workers, and those who are not participating in the labor market. As a result, it is correlated with individual characteristics that could bias estimates.

To create a measure of labor market conditions that is arguably exogenous at the individual level, we use the predicted employment growth rate which will replace the unemployment rate in Equation 2, following Bartik's (1991) "shift-share" approach.[13] This growth rate basically captures the exogenous (to the individual) changes in state labor demand. We classify total employment into 17 categories in the base year and calculate the share of each industry at the state level in the base period (1970). We also create the annual growth rate of each industry at the national level. We multiply the growth rate of each industry in a particular year with the corresponding share in the base period, and sum over industries to create the predicted employment growth for that particular year. Specifically, we define the employment growth rate (L_{st}) as:

$$L_{st} = \sum_{k=1}^{17} \varpi^k_{s,1970} \Delta N^k_t, \tag{2}$$

where $\varpi^k_{s,1970}$ is the share of employment in industry k[14] in state s in the base year and

[13]Schaller (2016) uses a similar approach to study the effect of the unemployment rate on the birth rate.

[14]We follow Schaller (2014) and Katz and Murphy (1992) to create 17 industry categories. We use the variable "IND1950" that uses the 1950 Census Bureau industrial classification scheme to consistently classify industries. The industry categories are: (1) Agriculture, Forestry and Fishing; (2) Mining; (3) Construction; (4) Low Tech Manufacturing; (5) Basic Manufacturing; (6) High Tech Manufacturing; (7)

ΔN_t^k is the growth rate of national employment in industry k in year t.[15] In other words, we weight the share of employment in each industry in each state by the growth rate of the corresponding industry at the national level, and sum over industries. We use the 1970 Census data to create the industry share in the base year.[16] In a robustness check, we also use the 1980 Census. To calculate the annual growth rate of the industry, we use the March Current Population Survey (CPS). For the March CPS, we use the survey weight to create the employment level for the total population for each year.

We also construct gender-specific employment growth rates, as male and female job market opportunities could affect children's educational outcomes differently. For example, the literature that attempts to understand the effect of parental job loss on children's educational outcomes mainly focuses on father's job loss. Father's job loss is expected to negatively affect children's educational outcomes. The effect of mother's job loss or unemployment is ambiguous. In the spirit of this literature, we can expect to have a positive effect of predicted male employment growth, while female's employment growth can have an ambiguous effect. To construct gender-specific employment growth rates (L_{gst}), we use the following approach:

$$L_{gst} = \sum_{k=1}^{17} \varpi_{gs,1970}^k \Delta N_t^k \tag{3}$$

where $g \in \{\text{male, female}\}$ and $\varpi_{gs,1970}^k$ is the ratio of each gender employment in an industry to the total employment of each gender in a state in the base year.

Using this data, we can modify Equation 1 by replacing the unemployment rate with

Transportation; (8) Telecommunications; (9) Utilities and Sanitary Services; (10) Wholesale Trade; (11) Retail Trade; (12) Finance, Insurance, and Real Estate; (13) Business and Repair Services; (14) Personal Services; (15) Entertainment and Recreational Services; (16) Professional and Related Services; and (17) Public Administration.

[15] We prefer the growth rate to the level of employment as the former is better able to capture labor market shocks. Additionally, growth rates are not sensitive to the size of states and are comparable across states.

[16] We prefer the 1970 Census to 1980 because variation in the "shift-share" approach is mainly driven by state industry shares in the base year (see Goldsmith-Pinkham, Sorkin and Swift 2018). Industry shares observed in 1970, a decade or earlier than the births of children in our sample, further mitigate any concern about the potential correlation between predicted employment growths and confounders of children's educational performance.

the predicted employment growths we created. This leads to the following model:

$$A_i = \alpha + \beta_1 L_{st} + \lambda X_i + \rho Z_i + \gamma_t + \varsigma_b + \psi_s + B_l + \epsilon_i, \tag{4}$$

where we can also replace L_{st} with L_{gst} and estimate the effect of employment or gender-specific employment growth in the year of a child's birth t. β_1 is the parameter of interest and it measures the effect of predicted employment growth (or gender-specific predicted employment growth) in the year of birth on children's math or reading scores. We cluster standard errors at the state-of-birth level. Clustering at both the state-of-birth and child level yields standard errors close to those of our baseline estimates. The main identifying assumption is that other unobserved factors that affect children's educational outcomes are not correlated with predicted employment growths in the year of birth. It is important to note that the major variation in our predicted growth rates stem from the base-year industry share. Hence, it is unlikely for contemporaneous business cycle or family decisions to bias our results. Further, it is worth noting that Dehejia and Lleras-Muney (2004) argue that high income families choose periods of high unemployment and low income families periods of lower unemployment to have a child. If such sorting takes place, our baseline model underestimates the effect, implying that the positive effect we find here is not attributable to the self-section. Nonetheless, to mitigate this potential concern that families may have self-selected a time for childbearing, we employ a mother fixed effects model in Section VI.

V. Results

A. First Stage Estimates

Before we estimate our main specification, we examine relationships between predicted employment growths and parents' labor market outcomes. We limit our analysis to parents of children whose standardized test scores are observable in our sample. The results are reported in Table A1. We find positive and significant effects for predicted male-specific employment growth on the number of weeks worked by fathers and fathers' wages in the year of the child's birth. One caveat of this analysis is that in our sample, fathers' labor market outcomes are reported by mothers and the sample has several missing values for these variables, especially earnings. We also look at the effect of predicted female-specific employment growth on mothers' labor supply and earnings in the year of the child's birth. Our estimates show a significant and positive effect on the number of weeks worked by mothers.[17] The effect on wage is insignificant.[18] It is worth noting that more than a third of the women report having zero weeks of employment in the calendar year of the child's birth. Additionally, we investigate whether gender-specific employment growths could affect family poverty status (Table A2). We find that an improvement in men's labor market opportunities reduces the likelihood of the family being in poverty in the year of the child's birth. However, we do not find a significant effect on poverty for female-specific employment growth. Additionally, we examine correlations between the unemployment rate and predicted employment growths. We present graphical evidence in Figure A1. Likewise, we regress the unemployment rate on predicted employment growths, separately, controlling for state and year fixed effects. As reported in Table A3, we find a statistically significant association between these.

As previously mentioned, we focus on reduced form estimates below for three reasons. First, for those children born after 1994, the data do not have parents' labor market outcomes in alternate years, as the survey is conducted biannually. Second, as the mother reports her spouse's labor market outcomes, they could be prone to measurement error. Third, predicted employment growth operates through multiple inputs to affect the achievement production function. As Todd and Wolpin (2003, 2007) and Cunha and Heckman (2007) discuss in

[17] The estimate is insignificant when we focus on the intensive margin of labor supply by conditioning our estimate on those having positive weeks of work.

[18] We also examine the effect of gender-specific employment growth on these labor market outcomes, controlling for a respective spouse's employment growth. The results are qualitatively similar.

detail, given the role of multiple inputs in child achievement, using instrumental variables is not an appropriate approach.

B. Main Estimates

We begin by estimating Equation 1 to examine the effect of the unemployment rate on children's math and reading scores. The results are reported in Table 2. The unemployment rate has a small positive effect on both math and reading scores. A one-percentage point rise in the state unemployment rate leads to a 0.002 standard deviation increase in math scores and a 0.009 standard deviation rise in reading scores. However, they are not statistically different from zero.[19] Though these estimates provide initial evidence of labor market conditions at birth on a child's test scores, this evidence is inconclusive. It is not surprising to have these findings, given that in theory, the effect of the unemployment rate in the year of birth on children's test scores is unclear. The unemployment rate is sensitive to both the composition of labor force and (non)participation in the labor force,[20] which could be correlated with other state- and individual-level unobserved factors that affect child development, both positively and negatively. For example, in a particular state, the number of individuals from certain groups (e.g., less-skilled or less educated) could change faster than the average in that state. It has been shown that for the less skilled/educated, the unemployment rate is higher than that of the overall unemployment rate. Hence, their disproportionate growth (decline) affects the state's unemployment rate differently. Further, their children are expected to have worse educational outcomes as compared to the average child. Therefore, any changes to a child's test scores associated with the unemployment rate could partly be ascribed to other unobserved family backgrounds rather than being the true effect of labor market conditions. Such a composition change may result in a negative association between

[19] Among control variables, we find a positive effect of age on math scores and negative effect on reading scores. We find it puzzling why we would have opposite effects of age on these test scores.

[20] Murphy and Topel (1997) using the Current Population Survey (CPS) data from 1968 to 1995, explain why the unemployment rate increasingly became a poor measure of labor market conditions.

the unemployment rate and a child's test scores.

Besides being prone to the individuals' withdrawal from the labor force, the unemployment rate is affected by participation in the labor force. For example, in the 1980s and 1990s, more women participated in the labor force on the back of decreasing discrimination against women in the labor market, which might have pushed the unemployment rate up. If that was the case, the unemployment rate might have increased even if the actual labor market conditions were improving. In that case, we should expect the positive relationship between the unemployment rate and a child's test scores.

As widely shown in the literature, the generosity of unemployment insurance (UI) benefits influences the unemployment rate, promoting individuals to stay unemployed longer. UI benefits are also shown to be helpful in children's education (Regmi 2019). In line with these strands of the literature, it could be argued that UI benefits are being positively correlated both with the unemployment rate and a child's test scores. Likewise, the aggregate unemployment rate could mask the differential effects of a father's and a mother's unemployment on child development. For example, Page, Schaller and Simon (2017) find that an improvement in a mother's employment opportunities lead to a decline in a child's health.[21] If these omitted factors were working in different directions as in theorey, we would expect the direction of bias in the OLS estimates to be ambiguous.

To address the limitation of the unemployment rate, we exploit labor demand shocks, as captured by the predicted employment growth rate described above, instead of the unemployment rate. Our estimates could be viewed as reduced form coefficients. We begin our analysis using the overall employment growth rate. As reported in Table 3, an improvement in overall labor market opportunities positively affects children's educational outcomes. A one-percentage point growth in the predicted employment rate during the year of birth in-

[21] Likewise, Lindo, Schaller and Hansen (2018), who study the effect of labor market conditions on child maltreatment using county-level data from California, show that the female-specific employment growth leads to a statistically significant increase in child maltreatment reports.

creases math scores of children aged 5 to 14 years by around 0.019 standard deviations, and reading scores by around 0.026 standard deviations.

It is well established in the literature that men and women's labor market conditions affect children's educational outcomes differently. For example, Rege, Telle, and Votruba (2011), using Norwegian register data, show that it is father's mental stress that is detrimental to children's educational performance. Table 4 shows our results. We find that better labor market opportunities for males significantly improve children's cognitive development. Furthermore, we find that female-specific labor market growth has positive effects on both math and reading scores. The magnitudes of these estimates are close to male-specific estimates. However, we cannot statistically distinguish these estimates from zero.[22] Weaker first-order effects of the predicted female-specific employment growth on labor market outcomes may have resulted in its statistically weaker effects on test scores.

In our analysis above, we examine the effect of male-specific employment growth on all children. However, for those children born to unmarried mothers, we would not expect child outcomes to be affected by improvement in men's labor market opportunities. Therefore, we also separated children by mother's marital status in the year of birth. We separately estimate the effect of male employment growth on children of married and unmarried mothers. Panel A of Table 5 contains the results. We do not find a statistically significant effect on the children of unmarried mothers. However, we find stronger effects for the children of married mothers. For comparison, we also examine effects of female-specific employment growth for the children of married mothers and unmarried mothers, separately. The estimates are statistically insignificant for both the groups (Panel B of Table 5). Our analysis on unmarried mothers could serve as a possible falsification check. If other unobserved factors were driving our results, we should expect to get a significant effect of the predicted male employment growth rate on children of unmarried mothers.[23] In summary, these results help corroborate

[22]We also estimate our model without controlling for mother characteristics. The results reported in Table B2 in Appendix B are qualitatively similar.

[23]As noted above, we focus on the cross-sectional sample for our analysis. In a robustness check, we

our identifying assumption that labor market shocks calculated in this paper are exogenous. For the rest of our analysis, we use children of mothers who were married during the year of birth of the child when we estimate the effect of the male-specific predicted employment growth rate. While investigating the effect of the female-specific employment growth rate, we continue to use the full sample.

C. Alternative Outcome

In this subsection, we examine the effect on an alternative outcome variable. We use the Peabody Picture Vocabulary Test (PPVT), which is typically administered to children ages 4 to 5 years and 10 to 11 years, through there are a few children from other age groups who took this test. We use all children under 15 years of age who took the PPVT. We separately estimate the gender-specific employment growth rates on the child's PPVT score. Table 6 contains the results. We find that improvement in labor market opportunities for men positively affects test scores. Our estimates show that a percentage point rise in the male-specific predicted employment growth rate in the year of birth increases the child's PPVT score by around 0.023 standard deviations. However, we find a comparatively lower magnitude when we use the female-specific employment growth rate, and the effect is not statistically different from zero. These findings strengthen our earlier estimates.

D. Home Environment

In order to understand the mechanisms through which improved/worsening labor market conditions in the birth year operate to shape children's cognitive development, we examine the effect on home environment in the year of birth. The NLSY79 Child and Young Adult contains three measures of home environment based on the Home Observation Measurement

estimate the effects for the full sample. We find the point estimates and standard errors similar to those of our baseline estimates.

of the Environment (HOME)-Short Form: (i) total HOME score, (ii) cognitive stimulation score, and (iii) emotional support score. These scores are calculated on the basis of responses from parents to questions related to the nature and quality of the child's home environment, which are considered to be crucial in a child's development. For example, it measures the availability of materials for learning and maternal acceptance of and involvement with her child, among others. We estimate the effect of the male-specific employment growth rate on all three measures. We report the results in Table 7. We find that increasing labor market opportunities for men lead to a significant improvement in overall home environment and emotional support. The psychology literature postulates that father's job loss creates a breakdown in the emotional relationship between father and child, adversely affecting the child's education (Elder, Nguyen and Caspi 1985 and Christoffersen 2000). In line with this literature, our results suggest that better emotional support to a child in the year of birth, stemming from an improvement in men's employment opportunities, positively affects a child's cognitive development.

E. Heterogeneity

Age. In this subsection, we examine if the effect of labor market shocks at birth fade with age. To understand the persistence of the effect, we divide data between two age groups: 5 to 10 years and 11 to 14 years. Table 8 contains the results. We find statistically significant effects on both math and reading sores for both groups of children.

Race. As seen in the literature, human capital formation patterns often differ by ethnicity and race. Therefore, we examine the effect by race: white, black, and Hispanic. As reported in Table 9, the effect is concentrated among white children. The coefficients are larger and standard errors are smaller for this group. For black and Hispanic children, we find insignificant effects. We also create race-specific employment growth rates for men. When we use these growth rates, our results are similar (Table B5).

F. Robustness Checks

In this subsection, we carry out additional robustness checks. First, we perform an analysis to examine whether pre-existing trends are driving our results. As in common in the empirical literature of event studies, we include several lags and leads of predicted male-specific employment growth in our main specification. In particular, we examine its effects at ages -3, -2, -1, 0, 1, 2, and 3. We present the coefficients in Figure A2 with 95 percent confidence intervals. We have insignificant effects prior to the year of birth and significant effects during the year of birth. The effects decrease after the first year.

Second, we examine whether or not subsequent labor market conditions could offset the effects experienced at birth. To do so, we re-estimate Equation 4 by including the average of the predicted male employment growth rates experienced by the child from the second year to the year of each survey (test-taking time). For example, if a child is surveyed at age eight, we calculate the average from the time s/he is two to seven. The results, reported in (Table 10), are similar to the baseline estimates.

Third, we estimate the effect of both male- and female-specific employment growths by including both types of employment growths in the same regression. This is intended to account for any other effect on child achievement arising from interdependencies in spousal labor supply. As reported in Table A4, using both gender-specific employment growths in our main specification produces point estimates of around 0.048 and 0.046 standard deviations for male-specific employment growth for math and reading, respectively. In comparison, the estimates in our main specification were around 0.033 and 0.032 standard deviations (Table 5) for math and reading, respectively. For female-specific employment growth, we continue to find statistically insignificant effects, but the signs of the estimates flip.

Fourth, as shown in Figure 1, most of the births in the sample occurred in the 1980s and 1990s. According to the Center for Human Resource Research (2002), most of the women had passed their primary childbearing age by 2000. The youngest woman in 2000 was 36 years old. It could be argued that births after 2001 occurred as a result of female childbearing postponement (or unintentionally) and children born after 2001 might be different from the average sample. To address this concern, we estimate Equation 4 by restricting the sample to children born before 2001 (Table A5). The results are consistent.

When we create the national growth rate of employment in an industry, we use the CPS March sample. Our time-series variation in the industry's growth at the national level comes from the employment observed in March. One possible concern is that those children who were born towards the end of the year could be less influenced by labor market conditions observed in March. To deal with this concern, we re-estimate our baseline model excluding children born after June. As presented in Table A6, we find stronger effects. Furthermore, we re-estimate our main findings using 1980 as the base year, applying the decennial Census 1980 data. We find similar estimates (available upon request).

Additionally, we re-estimate our main model by controlling for the lagged value of predicted male employment growth to control for serial correlation and other dynamics related to the labor market adjustment process (see Jaeger, Ruist and Stuhler 2018). We also control for state-level industry shares in the base year[24] in our main specification to address the possibility that our results are affected by the differential industry shares across states.

Finally, we re-examine the effect of the unemployment rate during the year of birth on children's cognitive development, instrumenting the unemployment rate by predicted male-specific employment growth. The results are presented in the Appendix (Table A8). Our estimates show that a higher unemployment rate negatively affects children's educational outcomes.

[24]When we use state-level industry shares, we must exclude birth year fixed effects. The results, which are reported in Table A7, are consistent.

VI. Self-Selection and Mother Fixed Effects

A potential concern with our identification strategy could be that parents, depending on their income, might react differently to local labor market conditions when it comes to their plan to have a child. There is a possibility that wealthy parents face higher opportunity costs of having a child during improved labor market conditions. As a result, they may decide to raise a child when the labor market faces slack. On the other hand, low-income or financially constrained families may prefer the timing of improvement in labor market conditions to raise a child, as their ability to provide necessary resources to the child improves. This is especially true when financial markets are not perfectly efficient and couples face borrowing constraints. Hence, we analyze whether highly and less educated mothers[25] respond differently to predicted labor market growths. We estimate the following model:

$$Birth_{jt} = \alpha + \beta_1 L_{g,st} * College_{jt} + \beta_2 L_{g,st} + \beta_3 College_{jt} + \lambda X_{jt} + \gamma_t + \psi_s + \epsilon_{jt}, \quad (5)$$

where $Birth_{jt}$ is an indicator variable if married mother j has a child under one year of age in calendar year t. This measures whether a mother gave birth to a child in the calendar year. $L_{g,st}$ is the male-specific predicted employment growth rate in state s in the calendar year t and $College_{jt}$ is a dummy variable that takes the value of one if a mother has a bachelor's degree or beyond. As reported in Table A9, we do not find evidence of self-selection into child bearing by predicted male-employment growth. We also estimate the differential effect of predicted female-specific employment growth for married mothers. We find an insignificant effect, suggesting that an improvement in female's labor market opportunities does not affect child bearing decision differently among highly and less educated married mothers. However, when we estimate the effect for single mothers, we find that higher educated mothers are less likely to give birth during improved labor market conditions compared to less educated mothers. Overall, our estimates suggest that our main findings–predicted

[25] We define highly educated mothers as those having a bachelor's degree or beyond.

male-specific employment growth positively affects children's cognitive development–are not driven by the sorting of women into giving birth by educational attainment.

In a further robustness check to examine if such sorting takes place and our results are potentially biased, we re-estimate our main model using mother-fixed effects. Specifically, we use the following model to examine the effect of predicted male employment growth on a child's cognitive achievement

$$y_{ij} = \alpha + \beta_1 L_{male,st} + \lambda X_{ij} + \rho Z_{ij} + \phi_j + \gamma_t + \varsigma_b + \psi_s + B_l + \epsilon_{ij}, \quad (6)$$

where i indexes child, j indexes mother, $L_{male,st}$ is the male-specific predicted employment growth rate in state s in the year of birth t, ϕ_j is a vector of mother-fixed effects and the remaining variables are defined as before. In this specification, we exploit variation within siblings. This controls for time-invariant family backgrounds and genetics, including family preferences with regards to timing of birth. As before, we restrict the sample to those children whose mothers were married at the time of birth. We report the results in Table 11. Our findings are qualitatively similar. This suggests that our baseline results are unlikely to be biased by parents' choosing the timing of child birth.

VII. Conclusion

We have presented evidence that local labor market conditions during the year of birth affect cognitive ability in childhood. To address omitted heterogeneity that jointly determine parents' labor market outcomes and children's development, we construct gender-specific predicted employment growth rates, following Bartik's (1991) "shift-share" approach. Specifically, we construct this measure by interacting the cross-sectional variation in an industry's share in state-employment in the base year with the growth rate of that industry at the national level. Our estimation focuses on examining children's math and reading scores when they are 5 to 14 years of age.

We find that improvement in male employment opportunities in the year of the child's birth helps improve cognitive ability during childhood. However, we do not find significant effects for women's improved labor market opportunities on a child's cognitive development. Our findings suggest the competing role of the income effect and parental care. Our results are robust to different specifications and alternative outcomes. We find a positive and significant effect for male-specific predicted employment growth on the Peabody Picture Vocabulary Test (PPVT) scores, but an insignificant effect for female-specific predicted employment growth. We find similar results using a mother fixed effects model that nets out time-invariant family backgrounds and other family characteristics.

Our findings carry important policy implications regarding the improvement of long-term prospects of children. In line with the extensive literature that shows the importance of early childhood education, one implication of this paper is that increasing social assistance during times of high unemployment might help shield children from adverse labor market outcomes. Likewise, the literature suggests that a father's health, especially his mental stress, is a major pathway through which his job displacement affects children's educational outcomes. Besides boosting transfer through social insurance programs such as unemployment insurance benefits, expanding health insurance coverage (both physical and mental) to the unemployed during labor market downturns could help lessen the the effect of labor market shocks on their children's cognitive development.

References

Aizer, Anna. 2010. "The Gender Wage Gap and Domestic Violence." *American Economic Review*, 100(4): 1847–59.

Allcott, Hunt, and Daniel Keniston. 2017. "Dutch Disease or Agglomeration? The Local Economic Effects of Natural Resource Booms in Modern America." *Review of Economic Studies*, forthcoming.

Barro, Robert. 2010. "The Folly of Subsidizing Unemployment." *The Wall Street Journal*, August, 30.

Bartik, Timothy J. 1991. *Who Benefits from State and Local Economic Development Policies?* W.E. Upjohn Institute for Employment Research.

Baum, Charles L. 2003. "Does Early Maternal Employment Harm Child Development? An Analysis of the Potential Benefits of Leave Taking." *Journal of Labor Economics*, 21: 409–448.

Becker, Gary. 1981. *A Treatise on the Family.* National Bureau of Economic Research, Inc.

Becker, Gary S, and Nigel Tomes. 1986. "Human Capital and the Rise and Fall of Families." *Journal of Labor Economics*, 4(3): 1–39.

Bernal, Raquel. 2008. "The Effect of Maternal Employment and Child Care on Children's Cognitive Development." *International Economic Review*, 49(4): 1173–1209.

Bernal, Raquel, and Michael P. Keane. 2011. "Child Care Choices and Children's Cognitive Achievement: The Case of Single Mothers." *Journal of Labor Economics*, 29(3): 459–512.

Bertrand, Marianne, Emir Kamenica, and Jessica Pan. 2015. "Gender Identity and Relative Income within Households." *Quarterly Journal of Economics*, 130(2): 571–614.

Black, Sandra E., Paul J. Devereux, and Kjell G. Salvanes. 2016. "Does Grief Transfer across Generations? Bereavements during Pregnancy and Child Outcomes." *American Economic Journal: Applied Economics*, 8(1): 193–223.

Blau, Francine D, and Adam J Grossberg. 1992. "Maternal Labor Supply and Children's Cognitive Development." *Review of Economics and Statistics*, 74(3): 474–481.

Buckles, Kasey S., and Daniel M. Hungerman. 2013. "Season of Birth and Later Outcomes: Old Questions, New Answers." *Review of Economics and Statistics*, 95(3): 711–724.

Center for Human Resource Research. 2002. "NLSY79 Child and Young Adult." *Columbus: The Ohio State University, CHRR NLS User Services.*

Christoffersen, M. N. 2000. "Growing Up with Unemployment: A Study of Parental Unemployment and Children's Risk of Abuse and Neglect Based on National Longitudinal 1973 Birth Cohorts in Denmark." *Child Development*, 7(4): 421–438.

Chu, C.-Y., Henderson D.J., and C.F. Parmeter. 2015. "Plug-in Bandwidth Selection for Kernel Density Estimation with Discrete Data." *Econometrics*, 3: 199–214.

Conti, Gabriella, and James Heckman. 2012. "The Economics of Child Well-Being." National Bureau of Economic Research, Inc NBER Working Papers 18466.

Cunha, Flavio, and James Heckman. 2007. "The Technology of Skill Formation." *American Economic Review*, 97(2): 31–47.

Dahl, Gordon B., and Lance Lochner. 2012. "The Impact of Family Income on Child Achievement: Evidence from the Earned Income Tax Credit." *American Economic Review*, 102(5): 1927–56.

Dehejia, Rajeev, and Adriana Lleras-Muney. 2004. "Booms, Busts, and Babies' Health." *Quarterly Journal of Economics*, 119(3): 1091–1130.

Denney, Jeffrey M., and Kristen H. Quinn. 2018. "Gestational Diabetes: Underpinning Principles, Surveillance, and Management." *Obstetrics and Gynecology Clinics of North America*, 45(2): 299 – 314.

Doblhammer, Gabriele, Gerard J. van den Berg, and Thomas Fritze. 2013. "Economic Conditions at the Time of Birth and Cognitive Abilities Late in Life: Evidence from Ten European Countries." *PLOS ONE*, 8(9): 1–12.

Dunn, Lloyd M., and Douglas M. Dunn. 1981. "Peabody Picture Vocabulary Test—Revised." Circle Pines, MN: AGS.

Elder, Glen H., Jr., Tri van Nguyen, and Avshalom Caspi. 1985. "Linking Family Hardship to Children's Lives." *Child Development*, 56(2): 361–375.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift. 2018. "Bartik Instruments: What, When, Why, and How." National Bureau of Economic Research 24408.

Hagedorn, Marcus, Iourii Manovskii, and Kurt Mitman. 2015. "The Impact of Unemployment Benefit Extensions on Employment: The 2014 Employment Miracle?" National Bureau of Economic Research Working Paper 20884.

Heijmans, Bastiaan T., Elmar W. Tobi, Aryeh D. Stein, Hein Putter, Gerard J. Blauw, Ezra S. Susser, P. Eline Slagboom, and L. H. Lumey. 2008. "Persistent epigenetic differences associated with prenatal exposure to famine in humans." *Proceedings of the National Academy of Sciences*, 105(44): 17046–17049.

Hilger, Nathaniel G. 2016. "Parental Job Loss and Children's Long-Term Outcomes: Evidence from 7 Million Fathers' Layoffs." *American Economic Journal: Applied Economics*, 8(3): 247–83.

Jaeger, David A, Joakim Ruist, and Jan Stuhler. 2018. "Shift-Share Instruments and the Impact of Immigration." National Bureau of Economic Research 24285.

James-Burdumy, Susanne. 2005. "The Effect of Maternal Labor Force Participation on Child Development." *Journal of Labor Economics*, 23(1): 177–211.

Kalil, Ariel, and Kathleen M. Ziol-Guest. 2008. "Parental employment circumstances and children's academic progress." *Social Science Research*, 37(2): 500 – 515.

Katz, Lawrence F., and Kevin M. Murphy. 1992. "Changes in Relative Wages, 1963-1987: Supply and Demand Factors." *Quarterly Journal of Economics*, 107(1): 35–78.

Lindo, Jason M., Jessamyn Schaller, and Benjamin Hansen. 2018. "Caution! Men not at Aork: Gender-Specific Labor Market Conditions and Child Maltreatment." *Journal of Public Economics*, 163(C): 77 – 98.

Murphy, Kevin, and Robert Topel. 1997. "Unemployment and Nonemployment." *American Economic Review*, 87(2): 295–300.

Ozabaci, Deniz, Daniel J. Henderson, and Liangjun Su. 2014. "Additive Nonparametric Regression in the Presence of Endogenous Regressors." *Journal of Business & Economic Statistics*, 32(4): 555–575.

Page, Marianne, Jessamyn Schaller, and David Simon. 2017. "The Effects of Aggregate and Gender-Specific Labor Demand Shocks on Child Health." *Journal of Human Resources*, forthcoming.

Pan, Weixiang, and Ben Ost. 2014. "The impact of parental layoff on higher education investment." *Economics of Education Review*, 42(C): 53–63.

Rao, Neel. 2016. "The Impact Of Macroeconomic Conditions In Childhood On Adult Labor Market Outcomes." *Economic Inquiry*, 54(3): 1425–1444.

Ravlić, Sanda, Nikolina Škrobot Vidaček, Lucia Nanić, Mario Laganović, Neda Slade, Bojan Jelaković, and Ivica Rubelj. 2018. "Mechanisms of fetal epigenetics that determine telomere dynamics and health span in adulthood." *Mechanisms of Ageing and Development*, 174: 55 –62.

Rege, Mari, Kjetil Telle, and Mark Votruba. 2011. "Parental Job Loss and Children's School Performance." *Review of Economic Studies*, 78(4): 1462–1489.

Regmi, Krishna. 2019. "Examining the Externality of Unemployment Insurance on Children's Educational Achievement." *Economic Inquiry*, 57(1): 172–187.

Ruhm, Christopher J. 2004. "Parental Employment and Child Cognitive Development." *The Journal of Human Resources*, 39(1): 155–192.

Schaller, Jessamyn. 2016. "Booms, Busts, and Fertility: Testing the Becker Model Using Gender-Specific Labor Demand." *Journal of Human Resources*, 51(1): 1–29.

Stevens, Ann Huff. 1997. "Persistent Effects of Job Displacement: The Importance of Multiple Job Losses." *Journal of Labor Economics*, 15(1): 165–88.

Tierney, Adrienne L., and Charles A. Nelson. 2009. "Brain Development and the Role of Experience in the Early Years." *Zero to Three*, 30(2): 9–13.

Todd, Petra E., and Kenneth I. Wolpin. 2003. *Economic Journal*, 113(485).

Todd, Petra E., and Kenneth I. Wolpin. 2007. *Journal of Human Capital*, 1(1): 91–136.

UNICEF. 2014. "Early Childhood Development. The Key to a full and productive life." https://www.unicef.org/dprk/ecd.pdf. Accessed 12 Novemeber, 2017.

van den Berg, Gerard J., Dorly J. H. Deeg, Maarten Lindeboom, and France Portrait. 2010. "The Role of Early-Life Conditions in the Cognitive Decline due to Adverse Events Later in Life." *Economic Journal*, 120(548): 411–428.

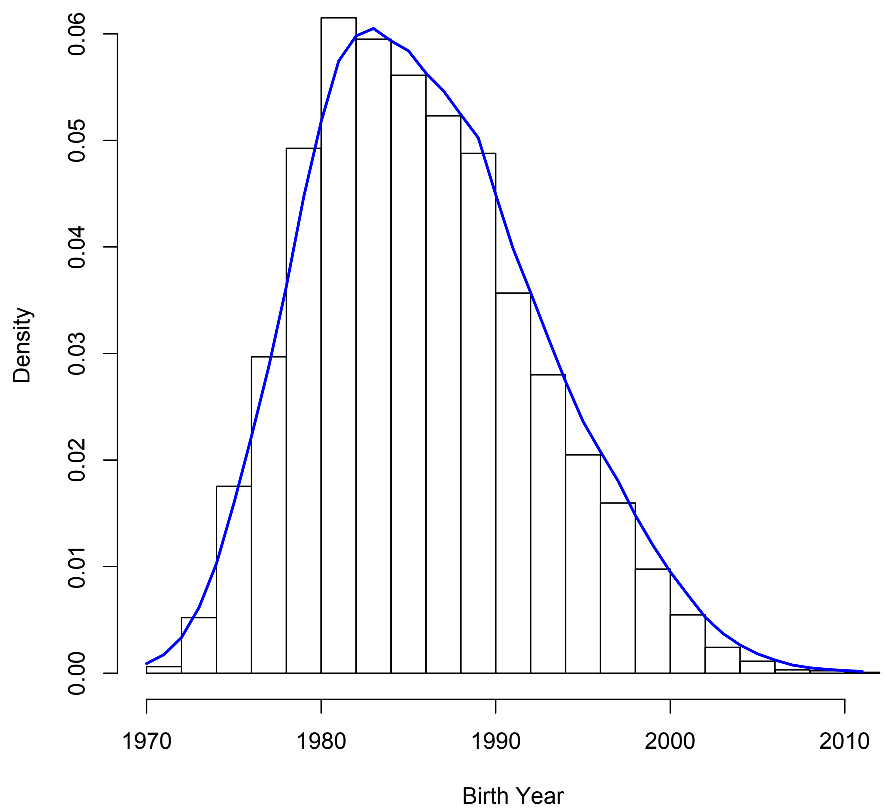
van den Berg, Gerard J., Maarten Lindeboom, and France Portrait. 2006. "Economic Conditions Early in Life and Individual Mortality." *American Economic Review*, 96(1): 290–302.

Waldfogel, Jane. 2002. "Child care, women's employment, and child outcomes." *Journal of Population Economics*, 15(3): 527–548.

Wang, Min-Chiang, and John van Ryzin. 1981. "A Class of Smooth Estimators for Discrete Distributions." *Biometrika*, 68: 301–309.

Woodhead, Martin. 2006. "Changing perspectives on early childhood: Theory, research and policy." Paper commissioned for the Education for All Global Monitoring Report 2007, Strong foundations: Early childhood care and education.

Figure 1: Distribution of Birth Cohorts in NLSY79 Child and Young Adult



Note: The kernel density estimate is obtained via the Wang and van Ryzin (1981) kernel function for ordered discrete data with plug-in bandwidth, see Chu, Henderson and Parmeter (2015).

Table 1: **Summary Statistics**

	N	Mean	Std. Dev.	Minimum	Maximum
PIAT Math	18519	0.306	0.960	-2.497	2.348
PIAT Reading	18460	0.224	0.957	-2.641	2.043
PPVT	7576	0.455	0.874	-3.458	3.371
Age	18602	9.655	2.752	5	14
Female	18602	0.490	0.500	0	1
White	18602	0.929	0.257	0	1
Hispanic	18602	0.022	0.145	0	1
Black	18602	0.050	0.217	0	1
Mother's Age	18602	36.898	6.231	0	56
Mother's AFQT	18602	52.112	28.342	0	100
Mothers with some College	18602	0.231	0.422	0	1
Mothers with College Degree	18602	0.249	0.433	0	1
Mother's Marital Status at Child's Birth	18602	0.767	0.423	0	1
Number of Siblings	18602	0.020	0.175	0	8
Predicted Emp. Growth Rate	18602	1.137	0.984	-1.503	4.095
Female-Specific Predicted Emp. Growth Rate	18602	1.304	0.887	-1.601	3.876
Male-Specific Predicted Emp. Growth Rate	18602	1.008	1.131	-2.876	4.515
Unemp. Rate	18602	6.815	2.215	2.300	17.792

Notes: Summary statistics are calculated using survey weights. The sample includes children ages 5 to 14 who have either non-missing PIAT math score or PIAT reading score. We normalize PIAT math, PIAT reading, and PPVT scores.

Table 2: **The Effects of the Unemployment Rate at Birth on Children's Cognitive Achievements**

	Math	Reading
Unemp. Rate	0.002	0.009
	(0.005)	(0.006)
Age	0.179***	-0.086***
	(0.020)	(0.021)
Age Squared	-0.009***	0.004***
	(0.001)	(0.001)
Female	-0.070***	0.144***
	(0.025)	(0.026)
Hispanic	-0.263**	-0.130*
	(0.100)	(0.077)
Black	-0.333***	-0.233***
	(0.040)	(0.048)
Mother's Age	0.008	0.013**
	(0.006)	(0.006)
Mother's AFQT	0.008***	0.008***
	(0.001)	(0.001)
Mother's Wage	0.008	0.004
	(0.013)	(0.011)
Mother with some College	0.064*	0.102**
	(0.033)	(0.040)
Mother with College Degree	0.278***	0.235***
	(0.051)	(0.039)
Mother's Marital Status	0.110***	0.119***
	(0.018)	(0.032)
Number of Siblings	-0.015	-0.048
	(0.037)	(0.037)
Observations	18,519	18,460
R^2	0.218	0.190
State-of-Birth Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Notes: The dependent variables are the PIAT math and reading scores of children aged 5 to 14 years. We normalize the scores. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table 3: **The Effects of Predicted Employment Growth at Birth on Children's Cognitive Achievements**

	Math	Reading
Predicted Emp. Growth	0.019*	0.026**
	(0.011)	(0.011)
Observations	18,519	18,460
R^2	0.218	0.190
Controls	Yes	Yes
State-of-Birth Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Notes: The dependent variables are the PIAT math and reading scores of children aged 5 to 14 years. We normalize the scores. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table 4: **The Effects of Gender-Specific Predicted Employment Growths at Birth on Children's Cognitive Achievements**

	Math	Reading	Math	Reading
Predicted Male Emp. Growth	0.018**	0.025***		
	(0.009)	(0.009)		
Predicted Female Emp. Growth			0.015	0.019
			(0.015)	(0.015)
Observations	18,519	18,460	18,519	18,460
R^2	0.218	0.190	0.218	0.190
Controls	Yes	Yes	Yes	Yes
State-of-Birth Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Notes: The dependent variables are the PIAT math and reading scores of children aged 5 to 14 years. We normalize the scores. Each column represents results from a separate regression. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table 5: **The Effects of Predicted Male Employment Growth at Birth on Children's Cognitive Achievements**

	Unmarried Mothers		Married Mothers	
	Math	Reading	Math	Reading
Panel A				
Predicted Male Emp. Growth	-0.011	0.017	0.033***	0.032**
	(0.018)	(0.025)	(0.010)	(0.012)
Observations	4,404	4,392	14,115	14,068
R^2	0.245	0.283	0.198	0.164
Controls	Yes	Yes	Yes	Yes
State-of-Birth Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes
Panel B				
Predicted Female Emp. Growth	0.007	0.020	0.024	0.024
	(0.025)	(0.032)	(0.016)	(0.019)
Observations	4,404	4,392	14,115	14,068
R^2	0.245	0.283	0.197	0.164
Controls	Yes	Yes	Yes	Yes
State-of-Birth Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Notes: The dependent variables are the PIAT math and reading scores of children aged 5 to 14 years. We normalize the scores. Each column represents results from a separate regression. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table 6: **The Effects of Gender-Specific Predicted Employment Growths at Birth on Children's Cognitive Achievements: An Alternative Outcome**

	PPVT	PPVT
Predicted Male Emp. Growth	0.023*	
	(0.012)	
Predicted Female Emp. Growth		0.017
		(0.045)
Observations	7,853	10,409
R^2	0.192	0.230
Controls	Yes	Yes
State-of-Birth Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Notes: The dependent variable is the Peabody Picture Vocabulary Test (PPVT) score of children aged 5 to 14 years. We normalize the scores. Each column represents results from a separate regression. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table 7: **The Effects of Male-Specific Employment Growth at Birth on Home Environment**

	HOME Score	Emotional	Cognition
Predicted Male Emp. Growth	0.092**	0.101**	0.051
	(0.036)	(0.047)	(0.044)
Observations	1,099	1,099	1,082
R^2	0.445	0.365	0.413
Controls	Yes	Yes	Yes
State-of-Birth Fixed Effects	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Notes: We estimate the effects of male-specific predicted employment growth on three measures of home environment separately. See the main text for detail. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table 8: **Heterogenous Effects by Age**

	Aged 5-10		Aged 11-14	
	Math	Reading	Math	Reading
Predicted Male Emp. Growth	0.035***	0.027**	0.032**	0.039**
	(0.011)	(0.014)	(0.013)	(0.015)
Observations	8,563	8,512	5,552	5,556
R^2	0.189	0.174	0.232	0.181
Controls	Yes	Yes	Yes	Yes
State-of-Birth Fixed Effects	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Notes: The dependent variables are the PIAT math and reading scores of children aged 5 to 14 years. We normalize the scores. Each column represents results from a separate regression. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table 9: **Heterogenous Effects by Race**

	White		Black		Hispanic	
	Math	Reading	Math	Reading	Math	Reading
Predicted Male Emp. Growth	0.034***	0.034**	-0.011	-0.035	0.020	0.049
	(0.010)	(0.013)	(0.073)	(0.056)	(0.025)	(0.046)
Observations	12,334	12,291	875	874	906	903
R^2	0.190	0.160	0.343	0.382	0.342	0.340
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State-of-Birth Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variables are the PIAT math and reading scores of children aged 5 to 14 years. We normalize the scores. Each column represents results from a separate regression. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table 10: **The Effects of Predicted Male Employment Growth at Birth on Children's Cognitive Achievements: Controlling for Shocks Later in Life**

	Math	Reading
Predicted Male Emp. Growth	0.033***	0.030**
	(0.010)	(0.012)
Observations	14,115	14,068
R^2	0.198	0.168
Controls	Yes	Yes
Controls for Subsequent Emp. Growth Rates	Yes	Yes
State-of-Birth Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Notes: The dependent variables are the PIAT math and reading scores of children aged 5 to 14 years. We normalize the scores. Each column represents results from a separate regression. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

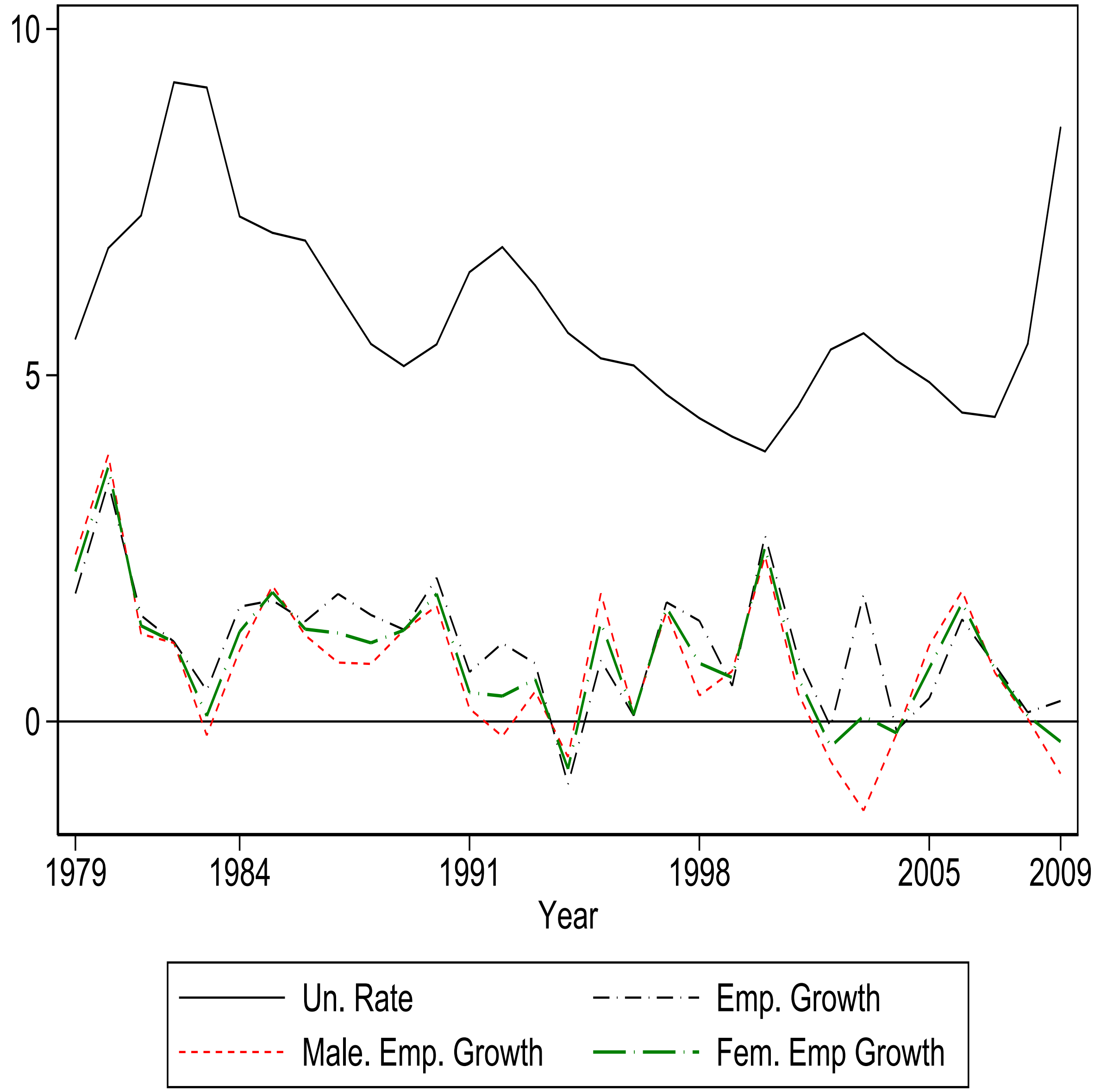
Table 11: **Mother Fixed Effects**

	Math	Reading
Predicted Male Emp. Growth	0.033**	0.043***
	(0.014)	(0.015)
Observations	14,115	14,068
R^2	0.526	0.546
Controls	Yes	Yes
State-of-Birth Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Notes: The dependent variables are the PIAT math and reading scores of children aged 5 to 14 years. We normalize the scores. Each column represents results from a separate regression. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

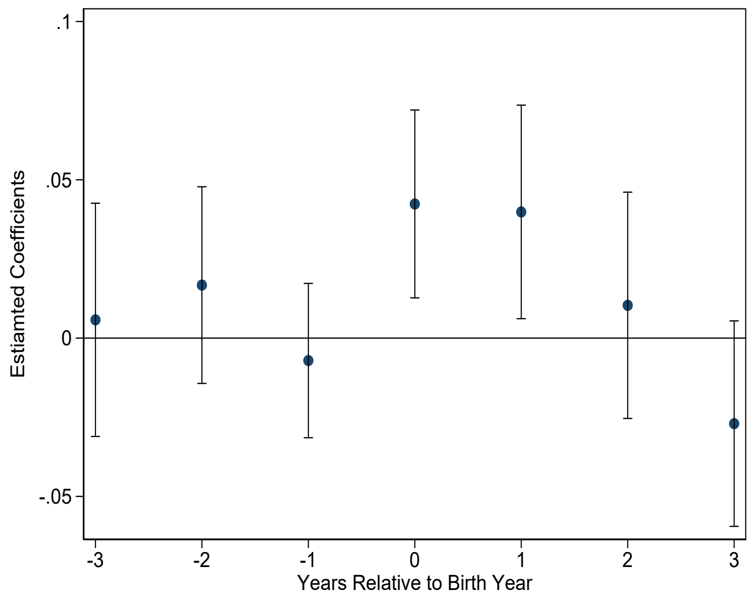
Appendix A

Figure A1: Relationship between the Unemployment Rate and Predicted Employment Growths

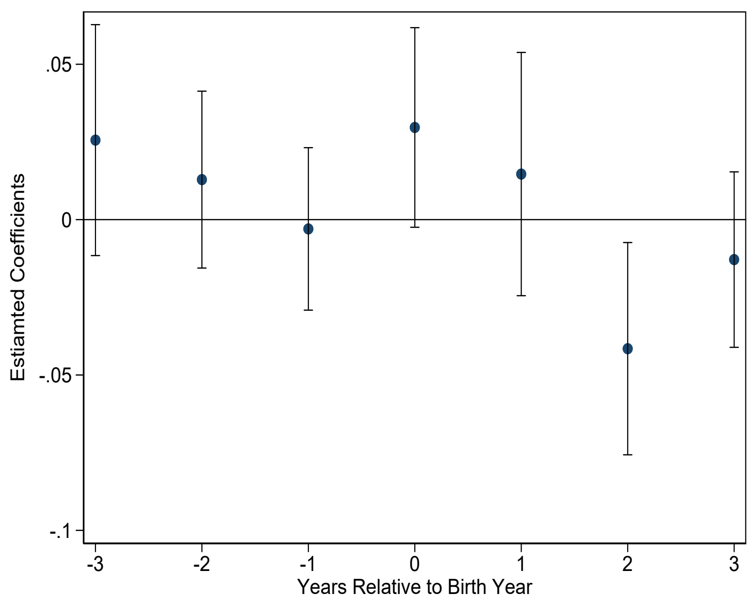


Note: The figure plots predicted employment growth, predicted male-specific employment growth, predicted female-specific employment growth, and the unemployment rate.

Figure A2: Effects on Math and Reading Scores



(a)



(b)

Notes: We estimate the effect of male-specific employment growth at ages -3, -2, -1, 0, 1, 2, and 3 on the children's PIAT math and reading scores. Figure (a) plots the coefficients and associated confidence intervals for math scores and Figure (b) for reading scores. 95 percent confidence intervals are derived clustering standard errors at the state of birth level.

Table A1: **Effects on Parents' Labor Market Outcomes**

	No. of Weeks	Wages	No. of Weeks	Wages
Predicted Male Emp. Growth	0.425*	0.035**		
	(0.227)	(0.017)		
Predicted Female Emp. Growth			1.530**	0.011
			(0.577)	(0.055)
Observations	3,200	2,717	4,017	2,447
R^2	0.071	0.234	0.215	0.321
Controls	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Notes: We estimate the effects of gender-specific employment growths on fathers' and mothers' labor market outcomes in the year of birth. Each column represents results from a separate regression. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table A2: **Effects on Family Poverty Status**

	Family Poverty	Family Poverty
Predicted Male Emp. Growth	-0.014**	
	(0.007)	
Predicted Female Emp. Growth		-0.011
		(0.013)
Observations	3,478	3,478
R^2	0.299	0.298
Controls	Yes	Yes
State Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Notes: The dependent variable is whether a family is living in poverty or not. Each column represents the results from a separate regression. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table A3: **Correlations between the Unemployment Rate and Predicted Employment Growths at Birth**

	Unemp. Rate	Unemp. Rate	Unemp. Rate
Predicted Emp. Growth	-0.415***		
	(0.079)		
Predicted Male Emp. Growth		-0.363***	
		(0.055)	
Predicted Female Emp. Growth			-0.202**
			(0.081)
Observations	1,581	1,581	1,581
R^2	0.766	0.768	0.760
State Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes

Notes: We analyze correlations between the unemployment rate and predicted employment growths. We use state-level data from 1979 to 2009, the birth period of children in our main analysis. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table A4: **Using both Male- and Female-Specific Employment Growths**

	Math	Reading
Predicted Male Emp. Growth	0.048**	0.046**
	(0.020)	(0.022)
Predicted Female Emp. Growth	-0.024	-0.022
	(0.031)	(0.035)
Observations	14,115	14,068
R^2	0.198	0.164
Controls	Yes	Yes
State-of-Birth Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Notes: The dependent variables are the PIAT math and reading scores of children aged 5 to 14 years. We normalize the scores. We use both male- and female-specific employment growths in the same regression. Each column represents results from a separate regression. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table A5: **The Effects of Predicted Male Employment Growth at Birth on Children's Cognitive Achievements: Limiting to Children Born Before 2001**

	Math	Reading
Predicted Male Emp. Growth	0.025***	0.029**
	(0.009)	(0.012)
Observations	13,794	13,748
R^2	0.206	0.168
Controls	Yes	Yes
State-of-Birth Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Notes: The dependent variables are the PIAT math and reading scores of children aged 5 to 14 years. We normalize the scores. Each column represents results from a separate regression. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table A6: **The Effects of Predicted Male Employment Growth at Birth on Children's Cognitive Achievements: Using Children Who Were Born Before July**

	Math	Reading
Predicted Male Emp. Growth	0.063***	0.062***
	(0.016)	(0.017)
Observations	7,270	7,247
R^2	0.214	0.195
Controls	Yes	Yes
State-of-Birth Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Notes: The dependent variables are the PIAT math and reading scores of children aged 5 to 14 years. We normalize the scores. Each column represents results from a separate regression. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table A7: **Additional Robustness Checks**

	Model (1)		Model (2)	
	Math	Reading	Math	Reading
Predicted Male Emp. Growth	0.036***	0.028**	0.034***	0.031**
	(0.011)	(0.011)	(0.010)	(0.012)
Observations	14,017	13,969	14,115	14,068
R^2	0.198	0.164	0.192	0.157
Controls	Yes	Yes	Yes	Yes
State-of-Birth Fixed Effects	Yes	Yes	No	No
State Fixed Effects	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes

Notes: The dependent variables are the PIAT math and reading scores of children aged 5 to 14 years. We normalize the scores. Each column represents the results from a separate regression. Model (1) further adds the lagged male-specific employment growth in our main specification as a control variable. Model (2) adds industry shares in the base year in our baseline specification. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table A8: **The Effects of the Unemployment Rate on Children's Cognitive Achievements: An Instrumental Variable Approach**

	Math	Reading
Unemp. Rate	-0.040***	-0.039***
	(0.012)	(0.014)
First Stage F-Statistic	384.62	399.59
Observations	14,115	14,068
Controls	Yes	Yes
State-of-Birth Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Notes: We estimate the effect of the unemployment rate in the year of child's birth on children's PIAT math and reading scores, using predicted employment growth as an instrumental variable. The scores are normalized. Each column represents the results from a separate regression. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table A9: **Effects on Fertility**

	Give Birth	Give Birth
Pred. Male Emp. Growth*Coll. Deg.	-0.002	
	(0.002)	
Pred. Male Emp. Growth	0.001	
	(0.003)	
Pred. Female Emp. Growth*Coll. Deg.		0.000
		(0.003)
Pred. Female Emp. Growth		0.006
		(0.005)
Coll. Deg	0.018***	0.017***
	-0.003	-0.003
Observations	36,448	36,448
R^2	0.066	0.066
Controls	Yes	Yes
State Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Notes: The dependent variable is whether or not a married mother gave birth in the survey year. If a mother reports having a child under the age of one year, we interpret this as mother giving birth in the survey year. Each column represents results from a separate regression. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Appendix B: Not for Publication

Alternative Measures of Outcomes. In our main analysis, we use a child-year as a unit of analysis, that is, we allow the labor market shock at birth to have effects on children's cognitive growth at different points of age during childhood. In this section, we consider having only one outcome for each child. To do so, we use two different approaches. First, we collapse test scores at the child level. Second, we use the first score of each child that we observe in our sample. As reported in Table B1, our results are consistent with those of the main sample.

Without Controls for Mother Characteristics. We extend our analysis by estimating the effect of predicted female employment growth without controlling for mother characteristics. We show in the main text that an improvement in women's employment opportunities has an insignificant effect on children's cognitive development. We further explore here if our estimates change when we do not control for mother characteristics. We use the specification parallel to Equation 5, except that we do not control for mother characteristics. The results, which are presented in Table B2, are consistent with our baseline estimates.

Additional Robustness Checks. To account for the fact that children are observed multiple times in our sample, we cluster our standard errors both at the state-of-birth and at the child level (Table B3). Table B4 presents the results estimated using state-specific linear trends.

Race-Specific Predicted Male Employment Growths. We construct the race-specific predicted male employment growths, using the following approach:

$$L_{male,rst} = \sum_{k=1}^{17} \varpi^{k}_{male,rs,1970} \Delta N^{k}_{t} \tag{7}$$

where $r \in \{\text{white, black, hispanic}\}$ and $\varpi^{k}_{male,rs,1970}$ is the ratio of each race male employment in an industry to the total male employment of each race in a state in the base year. We estimate the model analogues to Equation 5 in the main text. As shown in Table B5, the results are similar to those results derived from applying the general male-specific employment growth rate in the main text.

Table B1: **Alternative Measures**

	Model (1)		Model (2)	
	Math	Reading	Math	Reading
Predicted Male Emp. Growth	0.031***	0.029**	0.088***	0.036*
	(0.010)	(0.014)	(0.021)	(0.019)
Observations	3,466	3,465	3,454	3,404
R-squared	0.263	0.219	0.183	0.230
Controls	Yes	Yes	Yes	Yes
State-of-Birth Fixed Effects	Yes	Yes	Yes	Yes

Notes: In model (1), we average children's PIAT math and reading scores and use averages as dependent variables. Model (2) uses test scores that are observed for the first time for each child. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table B2: **The Effect of the Predicted Female Employment Growth Rate on Children's Cognitive Achievements: Without Controlling for Mother Characteristics**

	Math	Reading
Predicted Female Emp. Growth	0.016	0.021
	(0.014)	(0.015)
Observations	18,519	18,460
R^2	0.129	0.111
Controls	Yes	Yes
State-of-Birth Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Notes: The dependent variables are the PIAT math and reading scores of children aged 5 to 14 years. We normalize the scores. Each column represents results from a separate regression. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table B3: **Clustering Standard Errors at both the State-of-Birth and Child Level**

	Math	Reading
Predicted Male Emp. Growth	0.033***	0.032***
	(0.010)	(0.012)
Observations	14,115	14,068
R^2	0.198	0.164
Controls	Yes	Yes
State-of-Birth Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Notes: The dependent variables are the PIAT math and reading scores of children aged 5 to 14 years. We normalize the scores. Each column represents results from a separate regression. Standard errors are clustered at both the state-of-birth and child level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table B4: **Controlling for State-Specific Linear Trend**

	Math	Reading
Predicted Male Emp. Growth	0.031***	0.033***
	(0.010)	(0.012)
Observations	14,115	14,068
R^2	0.206	0.174
Controls	Yes	Yes
State-of-Birth Fixed Effects	Yes	Yes
State Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes

Notes: The dependent variables are the PIAT math and reading scores of children aged 5 to 14 years. We normalize the scores. Each column represents results from a separate regression. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.

Table B5: **The Effect of Race-Specific Predicted Male Employment Growth on Children's Cognitive Achievements**

	Math	Reading	Math	Reading	Math	Reading
Predicted Emp. Growth for White Men	0.034***	0.033**				
	(0.010)	(0.013)				
Predicted Emp. Growth for Black Men			0.005	-0.025		
			(0.066)	(0.056)		
Predicted Emp. Growth for Hispanic Men					0.021	0.032
					(0.027)	(0.043)
Observations	12,334	12,291	875	874	906	903
R^2	0.190	0.160	0.343	0.382	0.342	0.339
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State-of-Birth Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variables are the PIAT math and reading scores of children aged 5 to 14 years. We normalize the scores. Each column represents results from a separate regression. Standard errors are clustered at the state-of-birth level. * denotes significance at the ten percent level, ** denotes at the five percent level, and *** denotes at the one percent level.