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Francesco Agostinelli
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1126 E. 59th Street Box 107
Chicago IL 60637

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Money vs. Time: Family Income, Maternal Labor Supply, and Child Development*

Francesco Agostinelli[†] Giuseppe Sorrenti[‡]

Arizona State University University of Zurich

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[†]W.P. Carey School of Business, Department of Economics, Arizona State University (US). E-mail: fagostin@asu.edu

[‡]Department of Economics and Jacobs Center for Productive Youth Development, University of Zurich (CH). E-mail: giuseppe.sorrenti@econ.uzh.ch

Abstract

We study the effect of family income and maternal hours worked on child development. Our instrumental variable analysis suggests different results for cognitive and behavioral development. An additional $1,000 in family income improves cognitive development by 4.4 percent of a standard deviation but has no effect on behavioral development. A yearly increase of 100 work hours negatively affects both outcomes by approximately 6 percent of a standard deviation. The quality of parental investment matters and the *substitution* effect (less parental time) dominates the *income* effect (higher earnings) when the after-tax hourly wage is below $13.50. Results call for consideration of child care and minimum wage policies that foster both maternal employment and child development.

JEL classification: H24, H31, I21, I38, J13, J22

Keywords: Child development; Family income; Maternal labor supply

1 Introduction

Poverty represents one of the major threats to child development. In 2015, about 15 million children in the United States (21 percent of all children) were living in families with incomes below the federal poverty threshold (National Center for Children in Poverty, 2015). What effect does growing up in a disadvantaged family have on a child's achievements, and how can living conditions be improved to promote child development?

Support programs such as the Earned Income Tax Credit (EITC), the Food Stamp Program, and the Child Tax Credit attempt to reduce family poverty and especially that experienced by children. Many of these programs (e.g. the EITC) provide cash transfers on the condition that the recipient works (conditional cash transfers). Such conditions might shape child development by introducing a trade-off between the *income* effect, due to a surge in family income, and the *substitution* effect, due possibly to parental labor supply responses and a decrease in time parents spend with their child.

The arising trade-off poses an important question: is the change in family income more important than time spent with parents in shaping child development? In this study we answer this question by appraising the contemporaneous effect of changes in family income and maternal labor supply on cognitive and behavioral development of children. We implement an instrumental variable (IV) approach exploiting changes in the EITC benefits over time and shocks in the local labor demand as instruments for family income and maternal labor supply. In this sense, we bridge the gap between the literature dealing with the estimate of the effect of family income on child development and the literature on the effect of maternal labor supply and child-with-parents time. Moreover, we provide important insights on what policies can foster maternal employment and child development contemporaneously.

Family income is an important predictor of a child's success and future opportunities. Figure 1 shows the wide dispersion in children's achievements by family income. Both cognitive (Panel A) and behavioral (Panel B) development measures exhibit a steep income gradient, with high-achieving children placed in the top deciles of the after-tax family income distribution. The impact of family income on child development has been widely debated by economists. Previous studies such as Duncan et al. (1998), Levy and Duncan (1999), and Blau (1999) have found a positive relation between family economic conditions during childhood and child achievements. More recently, works such as Løken et al. (2012) and Dahl and Lochner (2012) employ instrumental variable techniques to confirm this positive effect in Norway and in the U.S., respectively.

In addition to studies regarding the income effect, a vast body of economic literature associates maternal labor supply during childhood with possible negative effects on child development and future opportunities (Baum, 2003; Ruhm, 2004; Bernal, 2008; Carneiro and Rodriguez, 2009; Bernal and Keane, 2011; Hsin and Felfe, 2014; Carneiro et al., 2015; Del Bono et al., 2016; Fort et al., 2017). As examples, according to Bernal and Keane (2011) each year of child care (versus maternal time input) before age 6 decreases test scores by 2.1 percent (0.11 standard deviations). Similarly, Carneiro et al. (2015) estimate that the probability of dropping out of high school decreases by 2 percent and wages increase by 5 percent at age 30 with the more time mothers spend with their children in the first months of life.

This paper reconciles these strands of the literature. For most families, an increase in income is due to an increase in maternal labor supply. In this case, a surge in monetary resources is associated with a potential decline in the time the mother spends with her offspring. To understand the possible trade-off between family income and maternal labor supply, we build upon the empirical model in Dahl and Lochner (2012) by considering not only the role of family income but also the role of maternal hours worked in shaping child development.[1] The work by Dahl and Lochner (2012) exploits quasi-experimental variation in the EITC to analyze the causal effect of family income on child achievement. However, the EITC is designed to incentivize individuals (including mothers) to work.[2] Mothers, and

[1]Dahl and Lochner (2017), after the analysis by Lundstrom (2017), adjust for a coding error in their previous work in the creation of the after-tax total family income. The results of the original and reviewed studies are similar.

[2]Hotz and Scholz (2003) and Nichols and Rothstein (2016) summarize theoretical and empirical findings

especially single mothers, are usually the main target group of these welfare programs and are most responsive to incentives (Meyer, 2002; Blundell and Hoynes, 2004; Blundell et al., 2016). This affects the maternal allocation of time between working and parenting, with potential effects on children's test scores. More precisely, endogenous labor supply responses affect child development through two channels. An increase in maternal hours worked generates an income effect, with additional resources coming from a boost in labor income. At the same time, changes in maternal hours worked can also generate a substitution effect, with changes in the time that mothers allocate to child care (Heckman and Mosso, 2014; Del Boca et al., 2014). Moreover, this paper is related to previous works that consider the effect of time and monetary resources on children by estimating a structural model of household choices and child development (see Del Boca et al., 2014; Mullins, 2016).

An additional contribution of our study relates to the broad definition used for child development. While many works (see Dahl and Lochner, 2012; Del Boca et al., 2014) exclusively focus on test scores for cognitive achievements, we extend the analysis to proxies for child noncognitive development.[3] As stated by Heckman and Rubinstein (2001), standard test scores only capture some of the multiple skills determining individual success and well-being. Moreover, early childhood interventions that boost personal traits such as self-discipline or motivation are usually deemed as extremely effective (Heckman, 2000). Socio-emotional skills are often more predictive of later-life success than cognitive skills.[4]

Our empirical analysis is based on the National Longitudinal Study of Youth 1979 (NLSY79) data set matched with its Children (NLSY79-C) section. This combined data set provides longitudinal information about measures of child development, family income, and hours worked by the mother. At the same time, the longitudinal structure allows

about the effect of the EITC on maternal labor supply. Blundell et al. (2016) analyze the case of the U.K. and find substantial elasticities for women's labor supply (in particular for the group of single mothers).

[3]We also explore features related to early childhood development (1–7 years old).

[4]For example, data from the Perry Preschool Program, a high-quality U.S. preschool education program, suggest that increased academic motivation generates 30 percent of the effects on achievement and 40 percent on employment for females. Reduced externalizing behavior decreases lifetime violent crime by 65 percent, lifetime arrests by 40 percent, and unemployment by 20 percent. Visit heckmanequation.org/resource/early-childhood-education-quality-and-access-pay-off/ for a discussion of these results.

us to account for individual unobserved heterogeneity through child fixed effects. Cognitive development is measured through children's achievements on the Peabody Individual Achievement Test (PIAT), a set of tests assessing proficiency in mathematics and reading. To study noncognitive development, we take advantage of the Behavior Problems Index (BPI). This comprehensive index is comprised of several different indicators for behavior such as aggressiveness or hyperactivity that are likely to shape children's future life opportunities.

Given the strong interdependence between maternal labor supply and family income, there is no suitable identifying source of variation that is likely to exclusively affect one variable of interest. Hence, in order to identify the single causal effect of either family income or maternal labor supply on child development, it is necessary to allow for the endogeneity of both inputs. To deal with this challenge, we exploit two instrumental variables. The first instrument is based on the longitudinal changes in monetary benefits of the EITC, one of the largest U.S. federal income support programs. This variation provides us with exogenous changes in family resources to allocate in child development. At the same time, only working people are eligible for EITC benefits, creating incentives for mothers to work. The second instrument is constructed by using longitudinal shocks in the local labor market demand. Shifts in local demand for labor affect equilibrium prices (wages) and, subsequently, the family income resources and the equilibrium labor quantity.[5]

Our instrumental variable analysis suggests different results for cognitive and behavioral development. An additional \$1,000 in family income improves cognitive development by 4.4 percent of a standard deviation.[6] The same income change has no effect on child behavioral development. An additional \$1,000 improves behavioral development by 1.3 percent of a standard deviation, and the result is not statistically significant.

[5]We provide evidence throughout the paper that both identifying sources of variation do not confound other contemporaneous state-specific factors, like state-specific trends in children's achievements or changes in the per-pupil financial resources of schools in different states. Moreover, in the spirit of Goldsmith-Pinkham et al. (2017), we assess the validity of our labor demand shock instrument by formally testing for any parallel pre-trends between the instrument and child development. We reject the hypothesis of the existence of any pre-trends.

[6]This result is in line with the findings of Dahl and Lochner (2012) and Dahl and Lochner (2017).

We find that the income effect is counterbalanced by a negative effect of hours worked by the mother on child development. An increase in maternal labor supply of 100 hours per year causes a statistically significant decrease in both child cognitive and behavioral development by approximately -6 percent and -5 percent of a standard deviation. The strong negative impact of the number of hours worked by the mother, both in terms of cognitive test scores and behavioral problems, encourages the debate in a new dimension: how to address concerns about the effect of maternal employment on child development.

We attempt to answer this question in the last part of our study. By using the time diary component of the American Time Use Survey (ATUS), we illustrate the mechanism underlying the negative impact of hours worked by the mother on child development. Similar to Sayer et al. (2004), Guryan et al. (2008), and Fox et al. (2013), we find that working mothers, conditional on income, invest less time in their children. As a consequence, labor market conditions play a role in shaping the effect of labor supply on child development.

We focus on the role of wages and show that, according to our results, an after-tax hourly wage up to $13.50 makes the substitution effect (less maternal time with the child) dominant over the income effect (higher earnings). With higher earnings, families face the option of substituting their decreased time investment with better and more productive alternatives (e.g. nonparental care, additional schooling, youth clubs, music activities, etc.).

We look for possible heterogeneous effects in different subgroups in order to highlight the potential importance of alternative inputs in the child development process. Behavioral development does not display evidence of heterogeneous impacts of income or hours worked by the mother. On the contrary, the negative effect of hours worked by the mother on cognitive development only appears in less educated, low-skilled, or single mothers. More educated and high-skilled mothers are likely to access to better nonparental child care options. Moreover, the differences in the labor supply effect can be reconciled with heterogeneous preferences for child care activities, generating different patterns of time allocation between working, child care, and leisure time (Guryan et al., 2008).

We further investigate these channels by comparing the investment in the child by maternal employment status and family income. The Child Development Supplement (CDS) of the Panel Study of Income Dynamics (PSID) collects detailed information about a wide set of children's activities and parental investment for a representative sample of U.S. families. Results obtained with this data set highlight some evidence of differential investments as a response to the maternal employment status when low-income families are compared to high-income families.

Policymakers might obtain several suggestions from our results. First, by showing the trade-off between the income and substitution effect in terms of child development, this work speaks to the growing body of literature about the effect of conditional versus unconditional cash transfers. Many income subsidies worldwide base monetary transfers on work requirements. In this context, only looking at the effect of income on child development might lead to biased policy predictions. Our results support the idea that policies aimed at fostering maternal labor supply can be beneficial to child development if integrated with specific consideration about a minimum wage or the taxation of family income. Alternatively, policies that encourage maternal employment in low-income families should also consider how to guarantee alternative sources of child care to support child development.

The remainder of the paper is structured as follows. Section 2 introduces the empirical model and the identification strategy. The data used for the analysis are presented in Section 3, while the results are described in Section 4. Section 5 sheds light on the mechanism underlying the main findings of the work. Section 6 concludes.

2 Methodology

2.1 Empirical Model

Child inputs strongly affect individual development and future opportunities. Our empirical model aims to capture the impact of family income and maternal hours worked on child development. We build upon the empirical model considered in Dahl and Lochner (2012) by including the hours worked by the mother as an additional explanatory variable for child achievement. Specifically, our child outcome equation takes the following form:

$$y_{i,t} = \beta_0 + \alpha_0\, t + \alpha_1\, I_{i,t} + \alpha_2\, L_{i,t} + x_i'\, \beta_{1,t} + x_{i,t}'\, \beta_2 + \eta_i + \epsilon_{i,t}\ , \tag{1}$$

where $y_{i,t}$ represents the child's outcome in period t.[7] In our empirical analysis, we focus specifically on both child cognitive and behavioral development. $I_{i,t}$ and $L_{i,t}$ reflect the after-tax total family income and the maternal labor supply (hours worked) at time t. x_i and $x_{i,t}$ represent exogenous observed family i fix and time-varying characteristics. η_i reflects unobserved family specific heterogeneity (which can capture any permanent unobserved family factor as well as child unobserved ability). We allow for an age-trend effect in children's outcomes (α_0). Finally, we define $\epsilon_{i,t}$ as the additional time-varying unobserved heterogeneity in the child's outcome, which may include unobserved child developmental shocks. Taking first differences to eliminate family fixed effects leads to the following empirical specification:

$$\Delta y_{i,t} = \alpha_0 + \alpha_1 \Delta I_{i,t} + \alpha_2 \Delta L_{i,t} + x_i'\beta_1 + \Delta x_{i,t}'\beta_2 + \Delta\epsilon_{i,t}\ , \tag{2}$$

where $\beta_1 = \beta_{1,t+1} - \beta_{1,t}$ allows us to control for differential growth in children's outcomes by observable characteristics (e.g. gender, age, race, etc.).[8] Equation (2) constitutes the baseline empirical model of this study, while α_1 and α_2 are the parameters identifying the income and maternal labor supply effect on child achievement. The coefficient α_1 expresses the effect of changes in family income on changes in child achievement, while α_2 captures the mother's labor supply effect on changes in child achievement.

To recover the parameters in equation (2) and to deal with the endogeneity of both family income and maternal hours worked, we implement an IV estimation strategy. Children

[7] We consider periods to be the child's age, and we use these two concepts interchangeably.

[8] The alternative, more general approach is to allow for a semiparametric model of differential age effects of observable characteristics on outcome growth by age.

from disadvantaged backgrounds are likely to experience contextual conditions affecting their development in the presence of substantial positive income shocks. Similarly, changes in maternal labor supply are likely to be linked to other unobservable characteristics affecting child development. Our IV approach tackles the endogeneity issues by exploiting two sources of exogenous longitudinal variation: (i) changes in the EITC benefits, one of the largest federal income support programs; and (ii) shocks in the local labor market demand.

2.2 Instrumental Variables

The identification of equation (2) is particularly challenging due to the endogeneity of both family income and maternal labor supply. Changes in family resources and *intra*-family labor market decisions can be correlated with family-specific unobserved permanent shocks, which threatens the validity of a standard OLS approach. We deal with this issue by implementing an IV approach based on two instruments: longitudinal changes in the EITC schedule, and longitudinal variation in labor demand shocks measured as geographical changes in sectoral compositions of local economies. The identification of the parameters in our linear specification in equation (2) requires two necessary conditions for the instruments: relevance and exogeneity. Here, we describe in detail the two instrumental variables. The discussion about the relevance of the instruments is postponed to Section 4.1, in which the results are presented.

2.2.1 Longitudinal Changes in EITC Benefits

When the EITC was introduced in 1975, it was a modest program that aimed to improve economic and social conditions of low-income families with dependent children. After its introduction, the EITC was progressively expanded (e.g. in 1986, 1990, 1993, etc.) to become the largest cash transfer program for low-income families with dependent children (Eissa and Liebman, 1996). In 2013, the total federal EITC reached $63 billion shared by 27 million individuals. In 2015, the program was responsible for lifting about 6.5 million people out of poverty, including 3.3 million children (Center on Budget and Policy Priorities, 2016).

The credit is conditioned on three eligibility criteria: (i) the taxpayer needs to report a positive earned income; (ii) the adjusted gross income and earned income must be below a certain year-specific threshold; and (iii) the taxpayer needs to have at least one qualifying child.[9] Therefore, the EITC's primary incentive is to increase the labor supply (Nichols and Rothstein, 2016). The provision of work incentives is typical of many welfare programs, and as shown in Blundell et al. (2016) in the U.K., mothers, and especially single mothers, are usually the most responsive target to these incentives.

As shown in Figure 2, the EITC income thresholds and benefits have changed over time. We plot the different amounts of received transfers conditional on after-tax family income, keeping all the family characteristics (e.g. marital status, number of dependent children, etc.) fixed. Focusing on a single year, it is possible to observe the structure of the EITC program and, specifically, the three phases that characterize the program. In the phase-in, the credit is a pure earnings subsidy. This is followed by a flat phase after which the credit starts to gradually phase-out. Individual incentives and behaviors regarding labor supply may differ according to the family structure and the position on the schedule. In particular, mothers who fall into the phase-out part of the schedule may have incentive to reduce their hours worked. However, Meyer (2002) provides evidence, at least for single mothers, that the past expansions in the EITC schedules did not show this type of response.

Figure 2 shows the EITC federal schedule expansions over time. Families with an after-tax income of around \$15,000 received a transfer of around \$1,000 in 1987 or 1989. The same families received an amount that was 400 percent higher (around \$4,000) in 1999. We exploit this variation of the EITC schedules over time to predict changes in family income and changes in maternal labor supply.

We start by showing the premise underlying the EITC's effects on our variables of interest. EITC benefits affect family income in two ways: (i) *directly* through the tax credit transfer;

[9] A few exceptions to the last criterion were introduced in 1994.

and (ii) *indirectly* through labor supply responses. Consider the following after-tax total family income ($I_{i,t}$) decomposition:

$$I_{i,t} = \underbrace{w_{i,t} \cdot L_{i,t}(EITC_{i,t}) + \widetilde{I}_{i,t}}_{I_{i,t}^{pre-tax}} + EITC_{i,t}(I_{i,t}^{pre-tax}) - \tau_{i,t}(I_{i,t}^{pre-tax}) \ , \tag{3}$$

where $I_{i,t}^{pre-tax}$ represents the pre-tax family income, composed of the mother's pre-tax earnings ($w_{i,t} \cdot L_{i,t}(\cdot)$) and other sources of income ($\widetilde{I}_{i,t}$). $EITC_{i,t}(\cdot)$ and $\tau_{i,t}(\cdot)$ represent respectively the EITC schedule and income tax schedule as a function of pre-tax family income.

The IV strategy is based on changes in the EITC schedules over time. However, directly using changes in received EITC benefits would make the instrument invalid as a change in the transfer that families receive is a function of both policy changes in the EITC schedules and the endogenous response in family income. Indeed, family income endogenously changes in response to several factors such as individual labor supply choices, changes in marital status or household structure, etc.

To exploit only policy changes in the EITC schedules, we construct the instrumental variable as in Dahl and Lochner (2012). We calculate the change in EITC benefits due to changes in the EITC schedules over time based on the predicted family income change that would have happened in any case, keeping fixed the family structure and characteristics to avoid possible endogenous changes in family composition and characteristics. In this way, our instrumental variable captures only the longitudinal variation in monetary benefits due to the changes in EITC schedules.

Specifically, our instrument takes the form:

$$\Delta EITC_{i,t}^{IV}\left(I_{i,t-1}^{pre-tax}\right) = EITC_{i,t}\left(\widehat{E}\left[I_{i,t}^{pre-tax} | I_{i,t-1}^{pre-tax}\right]\right) - EITC_{i,t-1}\left(I_{i,t-1}^{pre-tax}\right) \ , \tag{4}$$

where $\widehat{E}\left[I_{i,t}^{pre-tax} | I_{i,t-1}^{pre-tax}\right]$ represents the predicted family income as a function of lagged pre-tax income. We follow Dahl and Lochner (2012), and we use a fifth order polynomial of past income together with an indicator for positive lagged pre-tax income to predict current pre-tax income. For each family, the predicted changes over time in the benefits in equation (4) are now only a function of changes in schedules.

However, there is a possible concern underlying the definition of the instrumental variable in equation (4). In a cross-sectional perspective, differences in imputed changes in EITC benefits are explained by the previous period's pre-tax family income ($I_{i,t}^{pre-tax}$), as well as the predicted family income change ($\widehat{E}\left[\Delta I_{i,t}^{pre-tax}|I_{i,t-1}^{pre-tax}\right]$). We take into account this concern by introducing a control function for family income ($\Phi(I_{i,t-1}^{pre-tax})$) and augmenting our model specification as follows:

$$\Delta y_{i,t} = \alpha_0 + \alpha_1 \Delta I_{i,t} + \alpha_2 \Delta L_{i,t} + x_i' \beta_1 + \Delta x_{i,t}' \beta_2 + \Phi(I_{i,t-1}^{pre-tax}) + \Delta\epsilon_{i,t} \ . \tag{5}$$

With the inclusion of the income control function in the model, the validity of our first instrument relies on the assumption that no unobserved heterogeneity potentially correlated with lagged pre-tax family income is left. This condition translates into the following mean independence condition:

$$E(\Delta\epsilon_{i,t}|\Delta EITC_{i,t}\,(I_{i,t-1}^{pre-tax})) = 0 \ , \tag{6}$$

where $\Delta\epsilon_{i,t}$ represents the error term in equation (5). In other words, condition (6) assumes that our control function captures the true relationship between the expected unobserved heterogeneity and lagged pre-tax income. To fulfill this requirement, we introduce a generalization of the control function in Dahl and Lochner (2012) and we exploit a flexible Taylor expansion of $\Phi(\cdot)$ about the point of predicted income for a fixed EITC schedule change:

$$\begin{aligned} \Phi(I_{i,t-1}^{pre-tax}) \approx\ & \Phi\left(\widehat{E}\left[I_{i,t}^{pre-tax}|I_{i,t-1}^{pre-tax}\right]\right) \\ & + \sum_{n=1}^{k} \frac{\Phi^{(n)}\left(\widehat{E}\left[I_{i,t}^{pre-tax}|I_{i,t-1}^{pre-tax}\right]\right)}{n!} \cdot \left(\widehat{E}\left[I_{i,t}^{pre-tax}|I_{i,t-1}^{pre-tax}\right] - I_{i,t-1}^{pre-tax}\right)^n \ . \end{aligned} \tag{7}$$

The control function in equation (7) reconciles with the one implemented in Dahl and

Lochner (2012) in the limited cases in which they assume the control function to have the same functional form used to estimate the predicted family income ($n = 0$ order of approximation and $\Phi(I_{i,t-1}^{pre-tax}) = \widehat{E}\left[I_{i,t}^{pre-tax} | I_{i,t-1}^{pre-tax}\right]$).

Finally, we discuss a further possible threat related to the use of the EITC instrument. EITC changes may induce different responses in maternal labor supply for particular subpopulations. This can potentially compromise the monotonicity assumption of the instrument, which allows us to interpret the IV results as the local average treatment effect (see Imbens and Angrist, 1994). Monotonicity is an untestable assumption, but we focus on specific subgroups of our sample that have potentially different labor supply responses to EITC changes. Specifically, we separately focus on heterogeneous responses to the EITC with respect to lagged maternal employment status.[10] No evidence of possible nonmonotone responses to EITC changes arise in our framework, and all the results remain unchanged. At least in the above-considered dimension, our empirical strategy seems robust to potential heterogeneous responses in EITC changes.

2.2.2 Labor Demand Shocks

We use as a second instrument the spatial differential effects of long-term aggregate trends on local labor markets. Different local labor markets are characterized by different economic sectoral compositions, inducing different expositions to aggregate structural changes in the economy. Ideally, we would identify differences in exogenous labor demand changes, unrelated to the supply side, that shift the equilibrium of local labor market outcomes. We then could use this variation to predict changes in family income and mother's labor supply. Following the approach first developed by Bartik (1991) and used in many previous empirical works (see for example Blanchard and Katz, 1992; Autor and Duggan, 2003; Luttmer, 2005; Aizer, 2010; Notowidigdo, 2011; Bertrand et al., 2015; Diamond, 2016; Charles et al., 2015, 2017), we construct an empirical analogue of the above-mentioned thought experiment by

[10] Dahl and Lochner (2017) use a similar approach and allow for different effects for EITC changes relative to the mother's employment status.

considering the cross-state differences in industrial composition and aggregate growth in the employment level.

We exploit heterogeneous labor demand shocks for women by state and educational attainment. We define a group (or cell) "se" as the aggregation index for people living in a state s with a level of education e. For each variation unit se, we create labor demand shocks as national changes in industry-specific employment rates weighted by the industry female employment share at the baseline year. For our empirical analysis, we fix the baseline year at 1980, as our empirical analysis focuses on the period from 1988 to 2000 (see Section 3 for more details).[11]

Any observation i that belongs to the specific cell se is matched with the following instrumental variable value:

$$LabDemShocks_{i,t}^{IV} = \sum_{ind} (\ln E_{ind,-s,t} - \ln E_{ind,-s,1980}) \frac{E_{ind,se,1980}}{E_{se,1980}} , \tag{8}$$

where $(\ln E_{ind,-s,t} - \ln E_{ind,-s,1980})$ is (approximately) the percentage change in the aggregate employment rate in industry ind relative to 1980. To calculate this statistic for each state s, we consider all states except state s to avoid possible concerns of endogeneity (Goldsmith-Pinkham et al., 2017). $\frac{E_{ind,se,1980}}{E_{se,1980}}$ represents the 1980 female employment share of industry ind for a specific education group e in state s. The instrumental variable constructed in equation (8) can be interpreted as the average long-term growth in employment rates by state and educational achievement.

Figure 3 graphically shows the variation of labor demand we exploit. For the sake of clarity, we report only the first (1988) and the last year (2000) covered by our sample and two levels of educational attainment (high school dropout and college graduate). However, in the empirical analysis, we construct the instrumental variable for all years of our analysis and for four types of educational levels: high school dropout, completed high school, some

[11] Moreover, we choose the 1980 as the baseline year instead of an earlier decade as the earlier versions of census data sets are only 1 percent samples instead of 5 percent samples.

college, and completed college.

Figure 3 displays extensive changes in the employment rate over time and between different states. First, low- and high-educated mothers display opposite dynamics in employment rates. High school dropouts experience an overall decline in employment rate, with an average change of -0.34 percent from 1988 to 2000. On the contrary, the employment rate for college graduates increased by 0.40 percent from 1988 to 2000. Second, changes in employment rates from 1980 to 2000 are heterogeneous among states, with a standard deviation of 0.55 percent for low educated and 0.15 percent for highly educated women. The greatest declines in high school dropouts between 1988 to 2000 are shown in North Carolina, South Carolina, and Rhode Island, with a decline of -1.96, -1.80, and -1.68 percent, respectively. The greatest increases in employment rates for college graduate women are displayed in the District of Columbia, New York, and Massachusetts, with an increase of 1.41, 0.95, and 0.93 percent, respectively.

Conditional Independence. A recent paper by Goldsmith-Pinkham et al. (2017) shows that exploiting the labor demand shocks in equation (8) "is equivalent to using local industry shares as instruments, with variation in the common industry component of growth only contributing to instrument relevance." Hence, we can define our identifying assumption as the mean independence of the change in developmental, unobserved shocks ($\Delta\epsilon_{i,t}$) from 1988–2000 and the employment shares during 1980 for each state and education level:

$$E(\Delta\epsilon_{i,t}|LabDemShocks^{IV}_{i,t}) = 0 \ . \tag{9}$$

The condition in equation (9) does *not* state that cross-sectional differences in children's unobserved skills from 1988–2000 are uncorrelated with the state-specific employment shares in 1980. This last statement would be difficult to defend because of unobserved specific differences between states, which would directly affect the *level* of skills (e.g. school-quality differences) and would be potentially correlated with the industrial composition of that state.

Instead, our conditional independence condition points toward the dynamic aspect of child development, assuming that the unobserved *changes* in children's skills during 1988–2000 are uncorrelated with the state-specific industrial compositions in the U.S. in 1980.

To deal with some potential concerns underlying the condition in equation (9), we introduce an augmented specification of the model in equation (1) with potential state-specific trends in children's skills formation. In this way, we control for potential unobserved changes in state-specific factors that can affect the change in children's skills and, at the same time, can be confounding with the variation in local labor demand shocks (i.e. state-specific trends in school quality). All the results remain unaffected by the inclusion of state trends.[12]

Finally, following the suggestion in Goldsmith-Pinkham et al. (2017), we assess whether any parallel pre-trends between our instrumental variable and child development could jeopardize the validity of our identification strategy. Specifically, Goldsmith-Pinkham et al. (2017) recommend testing whether future values of the instrumental variable are predictive for the current second stage residuals. We do not find evidence of pre-trends.

Exclusion Restriction. The conditional independence is sufficient to interpret as causal the reduced form effect of labor demand shocks on child achievement. However, we need the *exclusion restriction* to hold in order to interpret our IV estimates as the causal effect of family income and labor supply. The exclusion restriction requires labor demand shocks to affect children's outcomes through either changes in after-tax family income or changes in maternal labor supply, and not directly in any other way.

One concern potentially undermining the exclusion restriction relates to the fact that local labor demand shocks might affect employment and the allocated resources in the education industry. We address this concern in Section 4.1 by showing that baseline results do not change if we augment the model with the change in per-pupil total revenues and per-pupil total current expenditures by state and over time. This evidence suggests that our instrument does not affect children's achievement through changes in the education system.

[12]See Section 4.1 for the analysis.

2.3 The Two-Stage Least Squares Estimator

We aim to estimate the causal impact of family income and maternal labor supply on measures for child development (y). We analyze child development by focusing on proxies for both cognitive and noncognitive development. Specifically, we exploit (i) individual scores in a combined math-reading standardized test as a proxy for children's cognitive development; and (ii) a standardized index for children's behavioral problems.[13] As discussed, we use longitudinal changes in the EITC schedule and longitudinal variation in labor demand shocks, measured as geographical changes in sectoral compositions of local economies, as instruments for family income and hours worked by the mother.

In this framework, for each of the endogenous variables $\Delta W \in \{\Delta I, \Delta L\}$ (changes in income or changes in hours worked by the mother), we estimate the following first stage:

$$\Delta W_{i,t} = \gamma_0 + \gamma_1 \Delta EITC^{IV}_{i,t} + \gamma_2 LabDemShocks^{IV}_{i,t} + x'_i\gamma_3 + \Delta x'_{i,t}\gamma_4 + \Phi(I^{pre-tax}_{i,t-1}) + \Delta u_{i,t} \ , \quad (10)$$

where i represents the child and t the time period. $\Delta EITC^{IV}_{i,t}$ is the change, with respect to the previous period, in the EITC schedule experienced by children i. $LabDemShocks^{IV}_{i,t}$ stays for labor demand shocks at time t (with respect to the baseline year 1980) experienced by children i in state s and with maternal education background e. To allow for differential growth rates in test scores in children with different (observable) characteristics, the vector X_{it} contains variables for children's gender, age, race, and number of siblings. The same vector also contains the third order polynomial control function for income previously discussed in Section 2.2.1. $\Delta u_{i,t}$ defines the error term (in difference). The second stage is:

$$\Delta y_{i,t} = \alpha_0 + \alpha_1 \widehat{\Delta I_{i,t}} + \alpha_2 \widehat{\Delta L_{i,t}} + x'_i\beta_1 + \Delta x'_{i,t}\beta_2 + \Phi(I^{pre-tax}_{i,t-1}) + \Delta\epsilon_{i,t} \ , \quad (11)$$

where $\widehat{\Delta I_{i,t}}$ and $\widehat{\Delta L_{i,t}}$ are the predicted changes in family after-tax income and hours worked by the mother obtained through the first stage estimates.

[13] We carefully introduce all details about the two outcomes of interest in the next section.

3 Data

The baseline empirical analysis exploits three different data sets: the National Longitudinal Study of Youth 1979 (NLSY79), the Current Population Survey (CPS), and the 1980 Census Integrated Public Use Microdata Series (IPUMS). While we could estimate the model using information only from the NLSY79, two potential concerns arise. First, the detailed level of heterogeneity in the construction of the labor demand shocks could suffer from small cell problems with the NLSY79 data. Second, this sample may not necessarily be informative of labor market conditions in later years at national or regional levels, as the NLSY79 is representative of U.S. Americans between 14 and 21 years of age in 1979. Therefore, we use the U.S. 1980 Census Data to calculate the employment share for each industry and group se at the baseline year (1980) and the longitudinal dimension of the CPS to compute the industry-specific changes in employment rates.

The National Longitudinal Study of Youth 1979 (and Children). Information about children and their families is obtained by matching the information of the mothers in the original National Longitudinal Study of Youth 1979 (NLSY79) to the additional children's survey (NLSY79-C). This matched data set (C-NLSY) results from a survey conducted every 2 years from 1986 to 2014. The sample selection rule adopted is simple; observational units are the children with information about the two main outcomes of interest, namely cognitive and behavioral development. Because the children are surveyed every two years, our empirical analysis of the model in equation (2) is based on 2-year changes (differences). In view of the above, our results should be interpreted as the effects of biennial changes in family income and maternal labor supply on biennial changes in children's cognitive and behavioral development.

Cognitive development is measured through achievements in math and reading activities. Specifically, we exploit the Peabody Individual Achievement Test (PIAT), a set of tests assessing proficiency in mathematics (math), oral reading and word recognition (reading recognition), and the ability to derive meaning from printed words (reading comprehension). We standardized each of the three test scores to obtain a measure with a mean of zero and a standard deviation of one.[14] We repeat the same procedure to compute an aggregate measure of math-reading achievement as the average of the three standardized single test scores.

The second outcome of interest is the Behavior Problems Index (BPI) score used as a proxy for children's noncognitive development. The BPI was created by Nicholas Zill and James Peterson to measure the frequency, range, and type of childhood behavior problems for children age four and older (Peterson and Zill, 1986). In the C-NLSY data set, five indicators for behavioral problems are collected: antisocial behavior, anxious behavior, headstrong behavior, hyperactive behavior, and peer conflicts behavior. Each index is transformed to obtain a positive scale so that higher values correspond to fewer behavioral problems. Hence, a higher index score corresponds to a higher-achieving (in terms of behavior) child. We standardize each single index to obtain a measure with a mean of zero and a standard deviation equal to 1.[15] We compute a comprehensive index, which is the mean of the five single indexes.

Information about child achievement and demographics is matched with family and mothers' information such as family income, marital status, education level, etc. We exclude from the analysis children whose mothers changed marital status in two consecutive periods. We want to avoid exploiting changes in family income that are due to changes in the presence of a husband in the family. We also restrict the analysis to the period between 1988 and 2000 for two main reasons: (i) to avoid mixing EITC changes with large changes in the U.S. tax system such as the Tax Reform Act of 1986 and the two tax cuts of 2001 and 2003; and (ii) to avoid confounding the aggregate effects of the great recession after 2007.

Finally, we use information about family income and the procedure introduced in Section 2.2.1 to compute both the after-tax family income and the federal EITC for each family and

[14]This standardization is made on the random sample of test takers. Obviously, for several reasons based on the sample selection rule adopted in our framework, not all these observations are part of the estimation sample.

[15]This standardization is made on the random sample of individuals reporting BPI indexes.

period by using the TAXSIM program by Daniel Feenberg and the National Bureau of Economic Research.[16]

The Current Population Survey (CPS). The CPS data set is representative of the U.S. civilian non-institutional population. We use an integrated version of the CPS from Integrated Public Use Microdata Series (IPUMS). This data set allows us to collect data about the yearly female employment rate for each cell se previously described in Section 2.2.2.

1980 Census Integrated Public Use Microdata Series (IPUMS). We use the 1980 U.S. Census data from IPUMS to construct in the most precise way the employment shares for the baseline year (1980) by industry, state, and education level. Census data contain enough observations to calculate the mean employment rate for each cell defined as the combination of industry, state of residence, and education level, and to deal with possible small cell problems.

Table 1 reports the descriptive statistics for the two main samples used in the baseline analysis, one for cognitive development as measured by the combined math-reading standardized test score, and one for the analysis of the BPI used as a proxy for noncognitive development. The two samples have similar characteristics.

The average performance on the math test is slightly more than 40 (out of 100) points, between 44 and 47 (out of 100 points) for the reading recognition test, and between 40 and 43 (out of 100 points) for reading comprehension. The average BPI is 3.2 for both samples.[17] The average family in the sample reports an after-tax income of around \$38,000 (median=\$31,000), while mothers spend on average around 1,200 hours per year working. Children are assessed biennially with PIAT tests and BPI tests starting at ages 5 and 4, respectively, until they reach the age of 18. Children in our estimating sample are, on average, approximately 10 years old. The sample is perfectly balanced in terms of gender, while it overrepresents ethnic minorities such as blacks (32–34 percent) and Hispanics (20

[16]TAXSIM is an ongoing project of Dan Feenberg of the NBER and his collaborators. It allows one to calculate "federal and state income tax liabilities from survey data." See Feenberg and Coutts (1993) for further details.

[17]Table 1 also shows the values for the single five components of the BPI score.

percent). Only 9 percent of the sample consists of an only child, 37–38 percent have one sibling, and 53–54 percent have two or more siblings. About 65 percent of mothers are married in both estimating samples. Finally, few mothers (8 percent) are college graduates; 71 percent have at most a high school diploma.

4 Baseline Results

4.1 The Effect of Family Income and Maternal Labor Supply on Child Development

4.1.1 First Stage Estimates

Table 2 illustrates the first stage results for both the math-reading test score (columns 1–2) and the BPI score (columns 3–4).[18] All the models, at both the first and second stages, are estimated by clustering standard errors at the family level to allow for serial correlation of the error term over time and between siblings.

The diagnostic tests for the first stage (bottom part of the table) suggest that the instruments work well in our specification for both the math-reading and the behavioral analysis. Neither under- nor weak identification seem to constitute a threat to our estimates.

We start by analyzing the first stage for family income. In terms of coefficients estimates, changes in the EITC schedule generate a positive effect on family income (columns 1 and 3). A $1,000 change in the schedule induces a $1,026 increase in after-tax family income when math-reading test score is analyzed and $1,101 when behavioral problems are considered. Our point estimates for the effect of changes in the EITC on family income are comparable with respect to those estimated by Dahl and Lochner (2017) and Lundstrom (2017).

Additionally, shocks in the labor demand positively affect family income. Indeed, a shift in the labor demand directly affects worker compensation and family resources. We find

[18] For the sake of brevity, we report here only a subset of the first stage coefficients. Table A.1 reports the entire set of first stage coefficients for individual characteristics.

that an increase by 1 percent in the employment rate relative to 1980 predicts an increase of \$1,659 (math-reading first stage) or \$2,067 (BPI first stage) in after-tax family income.

In columns (2) and (4) of Table 2 we present the first stage of hours worked by the mother. In our sample, the EITC schedule changes induce, on average, positive shifts in the maternal labor supply. The overall positive effect is generated from several different effects such as the differential impact on the extensive versus intensive margin or the differential effect for different subgroups of the population (Eissa and Liebman, 1996; Hoynes and Essa, 1996). A \$1,000 change in the EITC schedule explains an average increase of around 150 hours worked per year by mothers. The effect is similar for the math-reading sample (column 2) and the BPI sample (column 4). This effect is aligned with the findings in the EITC literature summarized in Nichols and Rothstein (2016): while earlier estimates indicated that the main effect of the EITC on labor supply was in terms of extensive margins, more recent studies have found evidence of nonzero, although small, intensive margin effects.

The second instrument labor demand shocks induce changes in hours worked. We find that a 1 percent change in the employment rate relative to 1980 induces a change of around 32 (24) hours worked per year by the mother. This means that, for the average mother who works 1,258 hours per year (see Table 1), a 1 percent change in the employment rate in her local labor market causes an increase of approximately 1.83 percent of her labor supply. The evidence from the first stage suggests that, in our sample, labor demand shocks affect both family income and maternal labor supply, although in the last case, the coefficient is only weakly significant.[19]

Two potential concerns need to be discussed in this framework. First, we neglect possible labor supply responses by the spouse, in the case of married couples, induced by EITC changes and shocks in the labor demand. The EITC literature previously estimated small changes for the male labor supply caused by EITC changes (Hotz and Scholz, 2003; Nichols and Rothstein, 2016). However, equation (2) includes this endogenous reaction as part of

[19]The coefficient is significant at the 10 percent level in the math-reading sample, while it is statistically insignificant in the BPI sample.

the error term, potentially jeopardizing our identification strategy. We analyze whether the instruments are predictive of changes in the spouse labor supply to test this hypothesis. We estimate our baseline first stage specification with changes in the spouse labor supply as dependent variable. Table A.2 reports the results. Neither changes in the EITC nor labor demand shocks in the women's labor market significantly predict changes in the spouse labor supply.

A second hypothetical concern relates to the possible existence of state-specific trends in children's skills formation that might constitute a threat to the exclusion restrictions. The conditional independence of the instrument based on labor demand shocks requires that unobserved *changes* in children's skills from 1988–2000 are not correlated with the state-specific industrial compositions in the U.S. in 1980. We estimate a model that augments the baseline with the inclusion of a full set of state fixed effects to capture state trends over time.[20] First stage diagnostic tests (see Table A.5) are improved when state fixed effects are also included in the baseline model. First stage coefficients remain almost unaltered in this new setting. This suggest that, even controlling for state trends in children's skill formation, our results do not change.[21]

4.1.2 Second Stage Estimates

Cognitive Development. We start by analyzing children's cognitive development as measured by the math-reading test score. Table 3 reports second stage estimates for the effect of family income and maternal hours worked.[22] Ordinary least squares (OLS) estimates in column

[20]The state-specific trends in model (1) become state fixed effects in our main specification (5). To see this point, consider our initial specification

$$y_{i,t} = \beta_0 + \alpha_{0,s}\, t + \alpha_1\, I_{i,t} + \alpha_2\, L_{i,t} + x_i'\, \beta_{1,t} + x_{i,t}'\, \beta_2 + \eta_i + \epsilon_{i,t}\ ,$$

where $\alpha_{0,s}$ is the coefficient for the state-specific trend. Taking the differences, we have

$$\Delta y_{i,t} = \alpha_{0,s} + \alpha_1 \Delta I_{i,t} + \alpha_2 \Delta L_{i,t} + x_i' \beta_1 + \Delta x_{i,t}' \beta_2 + \Delta\epsilon_{i,t}\ ,$$

where $\alpha_{0,s}$ is the state fixed effect in the difference model.

[21]We show below that second stage estimates are also unaffected by the inclusion of state trends over time.

[22]The full set of coefficients, including those for individual characteristics, is reported in Table A.3.

(1) suggest a weak and positive effect (0.1 percent of a standard deviation) of income on children's achievement, while the effect of hours worked is zero. These estimates suffer from various forms of bias. Unobserved dynamics in the quality of child care and family circumstances can correlate with the effect of family income and maternal hours worked on children's development. Furthermore, measurement error is likely to affect both the measures for income and for hours worked, generating potential attenuation bias for both estimates. Finally, Løken et al. (2012) show that, even in the absence of endogeneity, the OLS and IV estimands can be substantially different due to differential weighting of the marginal effects.

Instrumental variable estimates in column (2) address these concerns by correcting the endogeneity of family income and maternal hours worked. Family income positively affects child cognitive achievement. A $1,000 increase in family after-tax income, *ceteris paribus*, generates an increase of 4.4 percent of a standard deviation in the math-reading test score. This result, although a different estimation framework, is aligned with Dahl and Lochner (2017).[23]

Maternal hours worked induce a significant negative effect on children's performance. A 100-hour per year increase in maternal work, *ceteris paribus*, leads to a 6 percent of a standard deviation decrease in children's math-reading test score. The size of the effect is comparable with previous findings. Bernal (2008) finds that the mother's working full-time and using child care for 1 year is associated with a 1.8 percent reduction in the child's test score (0.13 standard deviations). Bernal and Keane (2011) estimate a 2.1 percent decrease in test score as response to one year of child care instead of (single) mother care.

This finding is important when it comes to analyzing the overall effect of changes in labor earnings on child development. Indeed, policies that foster maternal labor supply, like income transfers based on employment-status criteria, generate two opposing effects: a positive income effect and a possible substitution effect induced by parental hours worked. In the next sections, we carefully analyze the drivers of the negative effect of hours worked on

[23] This consideration also applies in the case of OLS estimates.

child development. The aim is to provide insights on how to design policies and interventions that contemporaneously foster maternal employment and child development. To anticipate the intuition, the effect of hours worked is driven by changes in parental inputs and in the quality of alternative sources of child care. Moreover, the wage rate plays a role in determining whether the income effect dominates the substitution effect of hours worked. Indeed, the wage paid shapes the marginal contribution of maternal hours worked in fostering family income.

Behavioral Development. Table 4 shows the analysis of behavioral development as measured by the BPI score.[24] OLS estimates display a close-to-zero effect of family income and a negative (-0.1 percent of a standard deviation), statistically insignificant effect of hours worked. IV estimates in column (2) suggest that the coefficient for family income is positive (1.3 percent of a standard deviation), although smaller than the one for cognitive development, and statistically insignificant. This result seems to suggest a differential impact of family income on the accumulation process of cognitive and noncognitive skills. While changes in family income considerably affect cognitive development, noncognitive development appears less sensitive (at least in the short term) to shocks in family income.

On the other hand, the effect of labor supply on noncognitive development fairly mimics the one for cognitive development. Maternal hours worked negatively affect child behavioral development. A 100-hour per year increase of maternal work causes a 5.2 percent of a standard deviation decrease in behavioral development.

The importance of accounting for the contemporaneous effects of family income and maternal labor supply on child development emerges with the analysis of the two factors in isolation. The analysis of family income without consideration of possible endogenous changes in labor supply creates a risk of underestimating the pure income effect on child development. At the same time, the analysis of labor supply without accounting for the induced income effect underestimates the (negative) effect of labor supply on child development.

[24] Table A.4 shows the full set of coefficients, including the ones for individual characteristics.

Table 5 shows the results of the analysis. In column (1), we use our identification strategy to estimate the effect of family income in isolation on children's cognitive development. The point estimate suggests an income effect of 1.7 percent of a standard deviation.[25] In terms of comparison with the baseline model of our study (column 3), the lower point estimate for the effect of family income in column (1) is hardly surprising. The coefficient for family income captures both the positive income effect on child development and the negative effect induced by one of the main determinants of positive income shocks, namely increases in individual labor supply. Behavioral development (columns 4 and 6) displays the same pattern. The coefficient for family income becomes considerably smaller in size, -0.3 versus 1.3 percent of a standard deviation, in the model using only family income as the endogenous regressor. The previous explanation for cognitive development also applies to this case.

Columns (2) and (5) focus on maternal hours worked in isolation. Coefficients display a smaller effect of maternal labor supply both for cognitive and behavioral development when compared to the reference baseline models in columns (3) and (6), respectively. For cognitive development, the effect switches from -2.1 to -6 percent of a standard deviation. For behavioral development, the change moves from -4 to -5.2 percent of a standard deviation. These changes confirm that the coefficient for maternal labor supply, when analyzed in isolation, captures both the labor supply effect and the positive income effect induced by increases in individual labor supply.

Given the strong interdependence between maternal labor supply and family income, there is no suitable identifying source of variation that is likely to exclusively affect one

[25] Dahl and Lochner (2017) find that the effect of an additional $1,000 of family income induces children's cognitive development to increase by 4.1 percent of a standard deviation. We replicate their empirical model with our estimating sample, and we find a comparable income effect of 2.5 percent of a standard deviation. We interpret the differences in estimates as the result of differences in the compliers' groups, as a result of different sample selection criteria. In fact, Dahl and Lochner (2017) trim the data according to whether families have a relatively large change in after-tax family income between two years (see the Online Appendix for specific details). These sample selection criteria are reasonable and well-motivated in the paper, given the authors' interest in analyzing the effect of marginal changes in family resources on child development. However, in our case, sizable changes in family income can be due to changes in the extensive margin of maternal labor supply. The latter represents a valuable identifying source of variation of the causal effect of maternal hours worked on child development if the extensive margin shifts are induced by our instrumental variables.

variable of interest. Hence, as shown above, in order to identify the single causal effect of either family income or maternal labor supply on child development, it is necessary to allow for the endogeneity of both inputs.

We will now discuss some potential threats to our IV framework validity. As introduced, the possible existence of state-specific trends in children's skill formation might undermine our exclusion restrictions. We take into account this potential concern by augmenting the model with state-specific trends in children's skills formation. Such inclusion does not affect the results.[26] Table A.5 shows that point estimates for the effect of changes in family income and hours worked are almost unchanged with respect to the models without state fixed effects. The replication of all the other analyses of the study including state fixed effects does not remarkably alter any of the results.[27] For this reason, we have decided to report in Table A.5 the baseline estimates obtained by including state fixed effects in the model, while in the rest of the work we report results without controlling for state fixed effects.

The exclusion from the set of regressors of variables capturing school financial and economic resources might bias our results by violating the exclusion restriction for the labor demand shocks instrument (see discussion in Section 2.2.2). In Table A.6, we deal with this potential concern by including changes over time of school finances and economic resources at the state level, therefore testing whether these variables were part of the error term of the model.

We use data about school resources from the CDD National Public Education Financial Survey, and we focus attention on two different measures.[28] First, we collect data on total revenues per pupil, measured as the total revenues from all sources divided by the fall membership. Second, we collect the total current expenditure per pupil, defined as the total current expenditure for public elementary and secondary education divided by the

[26]See Section 4.1.1 for the first stage analysis of this model with state-specific trends in children's skills formation.

[27]Results are available upon request.

[28]The CDD National Public Education Financial Survey has a primary purpose of making available to the public an annual state-level collection of revenues and expenditures for public education for students in prekindergarten through grade 12.

fall membership. We augment the baseline model by adding both variables expressed in difference with respect to the previous period.

Results highlight two main patterns. On the one hand, neither changes over time in revenues nor expenditures are statistically significant predictors of child cognitive and behavioral development. On the other hand, point estimates for both family income and hours worked by the mother are unchanged with respect to the specifications without controls for school financial and economic resources. Also first stage diagnostic tests, as shown by the tests in the bottom part of the table, are unaffected in this new model specification.

The work by Goldsmith-Pinkham et al. (2017) points out that, in general, labor demand shocks can include pre-trends that can indirectly affect the dependent variable, which may jeopardize the validity of our identification strategy. To test this hypothesis, Goldsmith-Pinkham et al. (2017) recommend testing whether future values of the instrumental variable are predictive for current second stage residuals. Table A.7 shows the hypothesis testing for the presence of pre-trends. We test for pre-trends with different specifications with different lagged variables, up to a maximum of 6 lagged years (3 model-periods as observations are collected every 2 years). We do not find evidence of pre-trends. In all cases, future labor demand shocks are not predictive of past child test scores. The only exception appears for the most adjacent case of the 1-period lag for cognitive measures. However, by extending the analysis to 2 periods or 3 periods of lagged variables, any relationship between future labor demand shocks and cognitive test scores arises.

Furthermore, as the instrument for labor demand shocks is state-specific, we address the potential concern due to possible endogenous household changes in state of residence from one period to another. In our sample, a very small fraction of families change their state of residence in two following periods.[29] To be conservative, we replicate our baseline analysis and restrict the sample to those households maintaining the same state of residence across

[29] In our estimation samples, there are 581 (math-reading sample) and 690 (BPI sample) cases of mothers who changed their state of residence during the two-year intervals when test scores and behavioral indexes are measured. In both cases, it represents approximately 5 percent of the entire sample.

two consecutive periods. The analysis in Table A.8 does not pinpoint any significant effect on results.

Finally, tax reforms may have heterogeneous effects within groups (Hoynes and Essa, 1996). Because of the structure of the EITC benefits, mothers who are working and fall into the phase-out section of the schedule may have incentive to reduce their hours worked, compromising the monotonicity assumption of the EITC instrument. This assumption is needed to interpret our IV results as the local average treatment effect (see Imbens and Angrist, 1994). Even if monotonicity is untestable, we consider the potential heterogeneous effects induced by the change in the EITC for employed versus non-employed mothers.[30]

Table 6 shows the results. First stage estimates do not provide any evidence of failure of the monotonicity assumption. The effect of changes in the EITC schedule on family income is positive both for employed and non-employed mothers. Shocks in the labor demand display a similar coefficient with respect to the one of the baseline analysis. Changes over time in the EITC benefits also positively affect maternal labor supply. Second stage results are similar to the ones in the baseline analysis. The effect of family income on the math-reading test score is positive and strongly significant, while maternal hours worked negatively affect the child's cognitive development. Additionally, the analysis of behavioral development (column 2) conveys the same message as the one in the baseline analysis of BPI.

In sum, this analysis shows that, at least in the above-considered dimension, we cannot reject the monotonicity assumption. Moreover, our results are not affected by using possible heterogeneous responses to changes in the EITC schedule as possible instruments for family income and maternal hours worked.

4.1.3 Decomposition of the Overall Effects

We focus here on the analysis of each single component of our aggregate measures for cognitive and behavioral development. Such decomposition is important as it allows us to

[30]Information about employment status refers to the previous period to mitigate possible endogeneity concerns.

understand whether the overall effect shown in the baseline analysis is general or is driven by some specific measures for children's achievements. Table 7 reports the decomposition of the combined math-reading test score in its three single components: math, reading recognition, and reading comprehension. The three tests in isolation confirm the existence of a positive and significant effect of family income on test performance counterbalanced by a negative impact of hours worked by the mother. The income effect appears slightly smaller in size (2.9 and 3 percent of a standard deviation) for math and reading comprehension (columns 1 and 3) when compared to reading recognition (column 2). In terms of hours worked, the effect is particularly sizable for reading recognition (-7 percent of a standard deviation) and reading comprehension (-4.9 percent of a standard deviation), while it is smaller for math (-3.6 percent of a standard deviation).

This evidence is suggestive of possible channels underlying the effect of maternal hours worked. At least two mechanisms potentially explain the results: (i) an endogenous reallocation of maternal time that values more schooling activities rather than reading; and (ii) a productivity gap of maternal time between math and reading.

We replicate the same decomposition analysis for indexes for behavioral development (Table 8). We analyze the following five components: antisocial behavior, anxious behavior, headstrong behavior, hyperactive behavior, and peer conflicts behavior. With the exception of hyperactive behavior (column 4), behavioral problems are not affected by family income. On the contrary, hours worked display a negative and significant (with the exception of anxious behavior in column 2) effect on behavioral problems, with point estimates bounded between -3.6 and -4.8 percent of a standard deviation.

The analysis of single behavioral indexes suggests similar insights with respect to the aggregate BPI index. Family income seems to play a very marginal role in shaping, at least in the short term, children's behavioral problems. Concurrently, the time spent with the mother is a relevant input in terms of children's behavioral development.

4.2 Early Childhood Development

Until this point we have considered measures for cognitive performance and behavioral problems for children older than 5 and 4 years old, respectively. We now extend the analysis to early childhood development. The C-NLSY data set contains information about temperament measures collected between ages 1–7. We focus our attention on three specific measures collected for children in this age range: compliance, insecure attachment, and sociability.[31] As for BPI, these measures are also expressed on a positive scale, meaning that higher values correspond to fewer temperament problems. We standardize each of the three measures to make an index with a zero mean and a unitary standard deviation. Because compliance and insecure attachment are collected for children in the same age range, we also construct an aggregate average index of the two.

Table 9 illustrates the analysis of the effect of family income and maternal hours worked on early childhood development. We estimate each model as in the baseline analysis. Despite the lower level of precision due to the reduced sample size, point estimates show a similar pattern to the one identified in the main analysis on older children.

The coefficient for family income is always positive and similar in size to that of the baseline model for the math-reading test score. For example, a $1,000 change in family income explains a (statistically insignificant) increase of 4.6 percent of a standard deviation in the compliance score (column 1). At the same time, the coefficients for maternal hours worked are negative, with a range between -1.0 (sociability, column 4) and -5.3 (compliance and insecure attachment, column 3) percent of a standard deviation. These magnitudes are similar to those found with respect to cognitive and behavioral development.

The analysis of early childhood provides supportive evidence that at this developmental stage there might also be a contemporaneous effect of family income and maternal hours worked on child development. The pattern seems to mimic the one identified for cognitive

[31] The NLSY79 contains other measures for child development in this age range. However, these are the only measures repeated over time, which therefore allow a dynamic analysis in first differences.

and behavioral development. Due to the limited sample size, the effects on early childhood development are not precise and require further analysis to infer more conclusive insights.

5 Hours Worked and Child Development: To the Roots of the Result

In this section we study the mechanisms behind the negative impact of maternal hours worked on child development. This understanding is crucial for designing policies that contemporaneously foster maternal employment and child development.

5.1 Time Investment in the Child

Parental inputs determine child development (Cunha and Heckman, 2008; Cunha et al., 2010; Del Boca et al., 2014; Heckman and Mosso, 2014; Agostinelli and Wiswall, 2016). The choice to increase maternal labor supply may generate a displacement effect in terms of maternal investment in the formation of children's skills. It is then important to establish whether maternal hours worked affect parental investment in the child.[32]

Time diary data allow us to observe maternal response in terms of time investment in the child as a result of her labor supply. We combine data from the American Time Use Survey (ATUS) and the American Heritage Time Use Survey (AHTUS), which provide information about the amount of time people spend doing various activities, such as paid work, child care, volunteering, and socializing.[33] For similarities with our estimating sample in the C-NLSY, we focus our attention on households with at least one child in the same age range of the baseline analysis in the period 1985–2003.[34]

[32]The mother, as a response to an increase of hours worked, may decide to decrease parental inputs and child investment or to decrease leisure activities to try to keep the amount of time devoted to the child fixed.

[33]See www.ipums.org/timeuse.shtml for further details.

[34]Our sample selection is based on the availability of the surveys. We start with the 1985 AHTUS. We use the 2003 ATUS to increase the sample size of the analysis.

We collect all the information about family income, hours worked by the mother, education of the mother, household composition (e.g. single-head household, number of children, etc.), child's age, and four measures of parental investment in child development. The available measures for parental investment are physical child care, helping with homework, reading and playing with the child, and a residual category containing other forms of child care. We also construct an aggregate measure that is the sum of the four mentioned child care activities. All the measures for time investment are expressed in hours per week.

Figure 4 shows the estimates of the five regressions of each time investment measure on family income and maternal hours worked plus a set of controls for mother's age, household composition, number of siblings, child's age, and year fixed effects. Each panel of the figure represents the regression coefficient, together with its 95 percent confidence interval, for maternal hours worked (Panel A) or family income (Panel B) on each measure for time investment in child care activities.[35]

As shown in Panel A, maternal hours worked are negatively correlated with parental time investment in all five considered activities. As an example, an increase of 1 hour worked per week predicts a 4-minute decline per week in child care time (total child care). In other words, the result is equivalent to an average decrease in child care of approximately 2 hours per week if the mother starts working full time (from 0 to 35 hours per week).

Panel B reports the results for family income obtained from the same models. All the coefficients are close to zero and statistically insignificant. In our sample, higher family income does not correlate with changes in parental time investment in the child. These results only suggest general insights; they do not deal with factors such as the quality of time parents spend with their children. Section 5.4 discusses that.

[35] It is important to recall that although the effect of maternal hours worked and family income are displayed in different panels, their coefficients are contemporaneously estimated with the same regression. Appendix Table A.9 shows the regression results.

5.2 Income versus the Substitution Effect: The Role of Wages

We exploit the results of the main analysis to explain the drivers behind the average negative impact of maternal hours worked on child development. An increase in maternal hours worked generates an income effect (higher earnings) and a substitution effect (displacement of maternal time) (Heckman and Mosso, 2014; Del Boca et al., 2014).

Given the specification in equation (1), the causal effect of maternal hours worked on child achievement can be deconstructed in these two mechanisms as follows:

$$\frac{\partial E\left[y_{i,t}|L_{i,t}\right]}{\partial L_{i,t}} \equiv \underbrace{\alpha_1 \cdot \frac{\partial E\left[I_{i,t}|L_{i,t}\right]}{\partial L_{i,t}}}_{\text{Income Effect}} + \underbrace{\alpha_2}_{\text{Substitution Effect}} . \tag{12}$$

By decomposing the total family income in the mother's after-tax earnings ($w_{i,t} \cdot L_{i,t}$) where $w_{i,t}$ represents the wage, and any other source of income ($\widetilde{I}_{i,t}$), we can rewrite equation (12) as:[36]

$$\frac{\partial E\left[y_{i,t}|L_{i,t}\right]}{\partial L_{i,t}} \equiv \alpha_1 \cdot \left(w_{i,t} + \frac{\partial E\left[\widetilde{I}_{i,t}|L_{i,t}\right]}{\partial L_{i,t}} \right) + \alpha_2 \; . \tag{13}$$

Equation (13) conveys a clear message: the effect of hours worked on children's achievement is ambiguous in sign and heterogeneous within the population. Given a wage rate $w_{i,t}$, the total effect in equation (13) depends on the relative magnitude of the income effect (α_1) in contrast to the substitution effect (α_2). Additionally, the income effect depends on the specific wage rate $w_{i,t}$, suggesting heterogeneous effects of maternal hours worked on children's outcomes. We investigate heterogeneity according to mother and child characteristics in the next section, while here we focus the attention on the role played by wages.

The effect of hours worked by the mother strictly depends on factors such as labor market conditions. The recognition of sufficiently high wages potentially overcomes the substitution

[36] This is the case when the mother is already working ($L_{i,t} > 0$). For the extensive margin case, the causal effect is $\frac{E[y_{i,t}|L_{i,t}]}{\partial L_{i,t}} = \alpha_1 \cdot \left(w^*_{i,t} + \frac{\partial E[\widetilde{I}_{i,t}|L_{i,t}]}{\partial L_{i,t}} \right) + \alpha_2$, where $w^*_{i,t}$ is the counterfactual wage she would receive once she works.

effect induced by decreased maternal time invested in child development. This is likely driven by the fact that the mother might be able to substitute her own input by purchasing higher quality alternative sources of child care (e.g. nonparental care, additional school, youth clubs, sport and music activities, etc.).

Figure 5 graphically shows the importance of the paid wage by exploiting our baseline results for the effect of maternal hours worked on child development.[37] The analysis assumes that other sources of income do not respond to changes in maternal labor supply, and the income effect is determined only by changes in earnings. The figure shows the heterogeneous effect of maternal hours worked on children's cognitive development with respect to maternal hourly wage. The intersection of the solid line (effect of hours worked) with the dashed horizontal line representing a zero net income-substitution effect, highlights that up to a corresponded wage of around \$13.50 per hour, the effect induced by the extra labor income (income effect) is not enough to compensate for the loss in child development induced by decreased maternal input (substitution effect). For wages higher than \$13.50 per hour, the income effect dominates the substitution effect.

In the background of Figure 5, we plot the wage distribution for both single and married mothers in our NLSY79 estimation sample, which provides an intuition on the determinants of the negative effect of maternal hours worked on child cognitive development. The biggest fractions of the wage distributions are located below the wage threshold corresponding to a zero or positive effect of maternal labor supply on child achievements. These results call for a policy discussion regarding the importance of labor market conditions and opportunities especially when it comes to women and, specifically, mothers. Moreover, such findings should spark a discussion on fiscal reforms and the minimum wage.

[37] The figure is based on the estimates in Table 3, column (2). As we do not find a significant income effect for behavioral development, we base this analysis exclusively on cognitive development.

5.3 Heterogeneous Effects of Maternal Hours Worked

In this section we replicate the baseline analysis by focusing on various subpopulations of interest. The aim is to understand whether the negative effect of hours worked on child development might be driven by differences in the quality of the alternative child care inputs used in substitution of maternal inputs or by other child characteristics such as race or age. Bernal and Keane (2011) show that informal care (grandparents, siblings, etc.) has adverse effects on child development as measured through test scores, and that more than 75 percent of single mothers use informal care. Mothers with a higher educational level or with higher skills are likely to use higher quality alternative inputs for their children, therefore possibly mitigating the negative impact induced by their increase in individual labor supply.

The analysis is based on five different sources of heterogeneity: maternal educational level, the Armed Forces Qualification Test (AFQT) as a proxy for maternal skills, maternal marital status, child's race, and child's age.[38] We compare maternal educational levels by dividing the sample in two groups: mothers with at most a completed high school degree (*Low education*) and mothers with some college education or more (*High education*). In terms of maternal skills, we separate mothers according to the median value of the AFQT test by labeling the ones with lower-than-the-median AFQT as *Low AFQT*, and those with higher-than-the-median AFQT as *High AFQT*. We analyze marital status by comparing married mothers with unmarried mothers. To take into account the possible differential effects of hours worked for minority populations, we also compare the white population with the black and Hispanic populations. Finally, the effect induced by maternal labor supply might be larger when the child is younger and needs more supervision and parental care. We look at potentially heterogeneous impacts of family income and maternal hours worked on child development according to child's age by dividing the sample into children under and over 12

[38] The Armed Forces Qualification Test (AFQT) was derived from the Army General Classification Test in 1950, and it is widely recognized as a reliable measure of mental ability. The AFQT score is not available for all the observations in the sample. Therefore, the sample size for this analysis is slightly reduced with respect to the one in the baseline models.

years old.[39]

Table 10 reports estimates by subpopulations according to mother's education (Panel A), AFQT score (Panel B), and marital status (Panel C). Column (1) displays the analysis of the combined math-reading test score. The differential impact of family income appears negligible. Coefficients are similar across subgroups for all sources of heterogeneity.[40]

The impact of maternal hours worked is indeed characterized by high heterogeneity. Considering maternal education as a source of heterogeneity, the negative effect of hours worked shown in the baseline analysis seems to be driven by the subgroup of mothers with a low educational level. For this group of mothers, an increase of 100 hours worked per year explains a decrease in standardized test scores by 5.8 percent of a standard deviation. The effect for the more educated counterpart is zero. The analysis of maternal skills and marital status unveils similar heterogeneous patterns. Maternal hours worked do not affect child cognitive development when mothers have high AFQT, while the effect of hours worked is negative and significant (-6.4 percent of a standard deviation) for low-AFQT mothers. Concerning marital status, the coefficient for hours worked is significant and negative (-6.9 percent of a standard deviation) for unmarried mothers, while the effect of maternal labor supply is statistically insignificant for married mothers.

The presented heterogeneous analysis suggests that parents from more advantaged backgrounds and with more resources, proxied by education, skills level, and marital status, might employ high-quality alternative inputs for the child when there is an increase in individual labor supply. Alternatively, they are able to more productively substitute the quantity of time with the quality of time devoted to their children.

The heterogeneous impact of maternal labor supply on child development is not confirmed

[39] To assess the importance of the heterogeneous treatment effects in our estimating sample, we decompose our predicted exogenous changes in our two endogenous variables in a two-stage least squares fashion, where we allow the second stage coefficients for income and hours worked to vary by mother's level of education, AFQT, marital status, child's race, and child's age. We implement a family-level clustered bootstrap procedure (100 repetitions) to adjust standard errors.

[40] A small but more pronounced difference appears for marital status, with unmarried mothers displaying a slightly larger effect than married mothers.

for behavioral development (Table 10, column 2).The effect of family income and hours worked is similar across groups. More precisely, any differential impact of maternal hours worked across subpopulations is detected neither for mother's education (Panel A), nor for mother's AFQT (Panel B), nor marital status (Panel C). These results suggest potentially different mechanisms underlying the cognitive and behavioral skill production functions. In particular, it is easier to substitute for parental time with activities related to cognitive development but more difficult to substitute for parental time with activities related to a child's behavioral development. Further research on this point is needed.

Table 11 extends the analysis to child characteristics. In terms of cognitive development (column 1), the analysis by race (Panel A) displays similar effects (around 4.6 percent of standard deviation) of family income across subgroups. We find a negative effect of maternal hours worked for both the subgroups of white and black or Hispanic. Although the point estimates across race subgroups are not significantly different, it is interesting to notice that the point estimate is larger in magnitude (-6.9 percent of a standard deviation) for black or Hispanic children than for white children (-4.7 percent of a standard deviation). Also the analysis by age (Panel B) highlights an interesting pattern. While the effect of family income is similar across age groups, the impact of maternal hours worked is more relevant for younger children (<12 years old). Relatively younger children report a statistically significant negative effect of maternal labor supply (-7.6 percent of a standard deviation), while the same coefficient is statistically insignificant and smaller (-5.3 percent of a standard deviation) for relatively older children. The evidence of heterogeneous impact by age suggests that the importance of parental input and investment in shaping child development is confirmed in all stages of childhood, although it seems to be dominant when the child is relatively younger.

When behavioral development is considered, child characteristics do not display heterogeneous patterns (Table 11, column 2). In general, the income effect is always statistically insignificant and similar across subpopulations. The effect of maternal hours worked is indeed negative and strongly significant for all the subpopulations of interest.

5.4 Employment, Child's Activities, and Quality of Child Care

Section 5.1 shows that maternal hours worked are negatively correlated with parental investment in child care. We analyze whether maternal employment status and family income play a role in explaining differences in the type and quality of investments. In particular, we investigate to what extent our heterogeneous results of maternal hours worked in Section 5.3 might depend on the quality of alternatives sources of child care.

We draw on data from the Child Development Supplement (CDS), a research component of the Panel Study of Income Dynamics (PSID), to analyze investment in child development.[41] In 1997, the PSID complemented its main data collection with additional information on 0-12 years old children and their parents. The aim was to provide researchers with a comprehensive, nationally representative, and longitudinal data set of children and their families with which to study the process of early human capital formation. We focus on the 1997 wave of the CDS (CDS-I) as it contains a wide set of information about parental investment in the child, child's activities, and time diary data for 3,563 children from 2,394 families.

Table 12 shows the analysis of a set of proxies for parental investment in child development. We compare values across four different subgroups of households: low-income and non-employed mother (LI,NE), low-income and employed mother (LI,E), high-income and non-employed mother (HI,NE), and high-income and employed mother (HI,E). This comparison allows us to disentangle: (i) differences in maternal investment and child's activities according to family income level, and (ii) the difference in investment and child's activities between employed and non-employed mothers conditional on family income. Low- and high-income families are defined according to the median value for family income in the CDS-I sample ($35,000). The employment status refers to the year 1997. The table reports average

[41]The PSID is a longitudinal study of a representative sample of U.S. individuals and the families in which they reside. Since 1968, the PSID has collected data on family composition changes, housing and food expenditures, marriage and fertility histories, employment, income, time spent on housework, health, consumption, wealth, and more. See psidonline.isr.umich.edu for further information about the data set.

values for the four subgroups (columns 1–4), together with the difference between employed and non-employed mothers conditional on income group (columns 5 and 7), and its statistical significance (columns 6 and 8).[42]

Panel A of the table depicts proxies for parenting styles. Behavior such as encouraging child's hobbies, showing physical affection, attending parenting classes, having the child cared for by others, or the use of rules to discipline the child display a similar pattern. Both low- and high- income families report insignificant changes across employment status (column 1(3) versus column 2(4)) or the change is similar across income groups (column 5 versus column 7).

On the other hand, diverging patterns arise in terms of monitoring activities perpetrated by parents. Low-income families put into practice more monitoring when the mother is employed. For example, employed mothers report higher levels of control over child's companions (+3 percent), activities after school (+6 percent), and homework time (+8 percent) when compared to the non-employed counterpart. Mothers with high incomes behave in the opposite way. In this case, we observe a decrease in investment for employed mothers (-11, -13, and -10 percent, respectively).

Panel B focuses on investment in their child's scholastic performance by parents. We observe a diverging pattern across income groups when we analyze activities such as contacting the faculty, keeping a closer eye on the child's activities, lecturing the child, encouraging the child to work harder, and helping the child with schoolwork. Results in column (6) highlight that any significant change is detected for low-income mothers. These mothers do not react differently to possible poor scholastic performance when they are employed as opposed to when they are not employed. Mothers from high-income families behave differently. They increase contact and discussion with faculty by around 7 percent (p-val=0.01) relative to

[42] Unless differently specified (e.g. in the case of a time diary), all variables in the table are constructed as dummy variables. The questionnaire contemplates "Yes/No" answers (e.g. encourage hobbies) for some of the investments or activities, while in other cases, a more detailed list of options is available (e.g. "Very likely", "Somewhat likely", "Not sure how likely", "Somewhat unlikely", "Not at all likely"). Appendix B.1 explains variable definitions and construction in detail.

non-employed mothers. They lecture their child more (+6 percent, p-val=0.04), and they prompt the child to work harder more often (+7 percent, p-val=0.04).

In Panel C, we analyze family environment scales to describe the environment to which each child is exposed. Scales are obtained as the combination of information collected in the data set (e.g. parental reaction to child's behavior, ways of showing physical affection to the child, etc.).[43] Four different scales are available: the general home scale, the cognitive stimulation scale, the emotional support scale, and the parental warmth scale. High-income families outperform low-income families. Concerning the maternal employment status, we find that the presence of employed mothers is almost always correlated with an increase in home scales. The increase is similar across income groups, although slightly larger in size for low-income families.

Finally, in Panel D of the table we use time diary data to study differences in the daily activities of the child. School attendance is similar across income groups. In general, children from families with non-employed mothers attend less school (around 12,000 seconds per day) than children with employed mothers (around 16,000 seconds per day). If the average school quality differs across income groups (e.g. high-income mothers living in better neighborhoods with high quality schools, etc.) this might produce a differential effect related to maternal employment.

We then focus on activities usually considered as potentially detrimental for child development.[44] Time spent watching television highlights an interesting pattern: in both income groups, children with employed mothers tend, or at least declare, to watch less television. This is probably due to a lower amount of time spent at home. However, while the average decrease in television watching in low-income families is 221 seconds per day, the same decrease is double for children from high-income families (522 seconds per day).[45] Similarly, maternal

[43] Refer to psidonline.isr.umich.edu and to the CDS-I User Guide Supplement for additional information about the construction of family environment scales.

[44] A consistent fraction of individuals in the sample report zero seconds for such activities; this explains the apparently low average values displayed in the table.

[45] These values are statistically insignificant for both income groups.

employment is correlated with an increase in the time spent playing electronic games exclusively for the subgroup of children from low-income families. Indeed, the employed versus non-employed differential is sizable (+172 seconds per day, p-val=0.10) for children from low-income families, while it is close to zero and statistically insignificant (+27 seconds per day, p-val=0.73) for children from high-income families.

Educational activities, such as art and sculpture, highlight an opposite income-related pattern. Children from high-income families do not display any significant change due to maternal employment status (-30 seconds per day, p-val=0.56), while a significant decrease arises for low-income families when employed and non-employed mothers are compared (-119 seconds per day, p-val=0.01). The change in time devoted to reading and looking at books is similar across employment statuses for both income groups. Children from low-income families tend to increase the time devoted to visits to other persons as a response to maternal employment relatively more than children from high-income families.

The evidence in this section suggests potential differential patterns in the quality of investment in child development for employed and non-employed mothers across income groups. Employed, high-income mothers tend to substantially decrease their control over their child's activities (when compared to their high-income, non-employed counterpart), unless they become aware of their child's poor academic performance. Low-income mothers behave in the opposite way by increasing control as a response to employment (lower trust in the alternative inputs used). Moreover, children from low-income families seem to engage more with respect to their wealthier counterparts in activities potentially detrimental for their development as a response to maternal employment. These results might help explain the overall effect of maternal hours worked on child development and the stronger impact of labor supply (on cognitive development) for mothers from low socio-economic backgrounds.

6 Conclusion

This paper unveils the contemporaneous effect family income and maternal hours worked have in shaping child development. We combine the analysis of cognitive and noncognitive development. We exploit children's performance on standardized tests to measure cognitive development. We use indicators of behavioral problems to gauge noncognitive development.

We find that family income has a sizable and positive effect on cognitive development, while the income effect is negligible (although positive) on behavioral development. The effect of maternal hours worked is the same across outcomes. On average, hours worked by the mother negatively affect both cognitive and behavioral development.

We shed light on the mechanism behind the negative effect of maternal hours worked on child development. Working mothers invest less time in child care. As a consequence, the choice of alternative sources of child care becomes crucial; this choice is likely to be affected by economic factors. We decompose the overall effect of maternal hours worked on child development into an income effect (higher earnings) and a substitution effect (less maternal time). We find that the substitution effect tends to dominate the income effect when the after-tax hourly wage is less than \$13.50 per hour. With higher earnings, families are able to substitute their decreased time investment with better and more productive alternatives. In line with this explanation, we show that the average effect (on cognitive development) is mainly driven by low-income, less-educated families and that the employment effect on investment in the child differs according to family income.

Several policy suggestions derive from our results. The trade-off between the income and substitution effect in terms of child development encourages a debate about the effect of conditional versus unconditional cash transfers. Income subsidies that provide monetary transfers based on work requirements might produce heterogeneous impacts in terms of child development. Our analysis confirms that policies aimed at fostering maternal labor supply benefit child development when considered in conjunction with well-researched policies concerning the optimal level of family income taxation or the optimal minimum wage.

Alternatively, policies that encourage maternal employment in low-income families should also guarantee alternative sources of child care to support child development.

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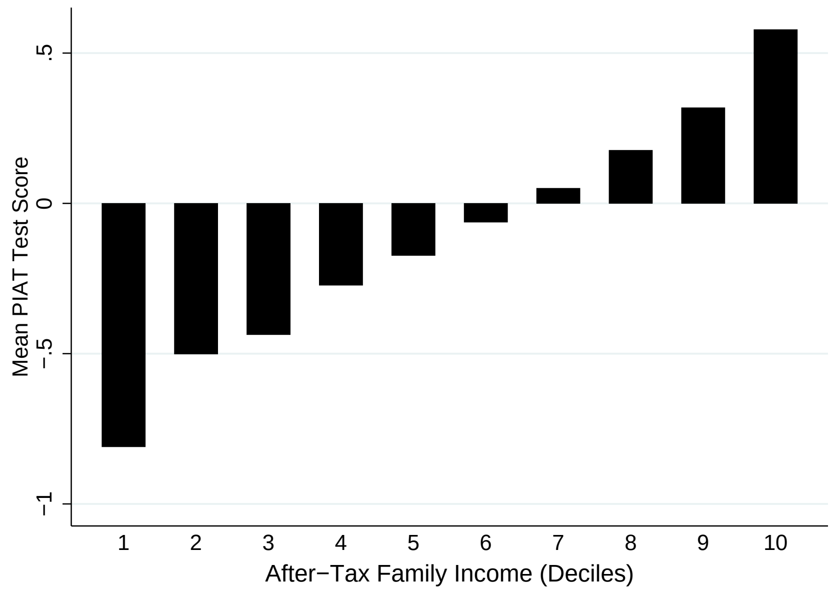
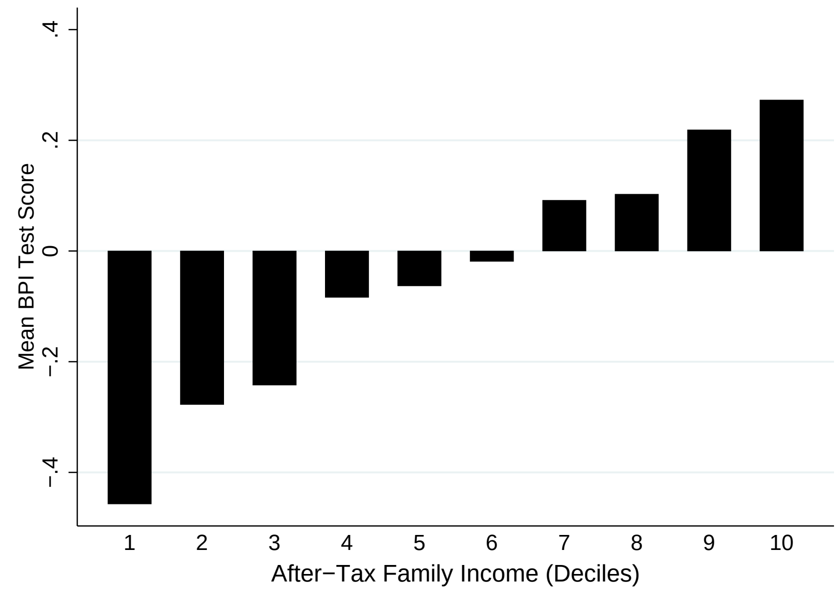
Figure 1: Children's Outcomes by After-Tax Family Income Deciles



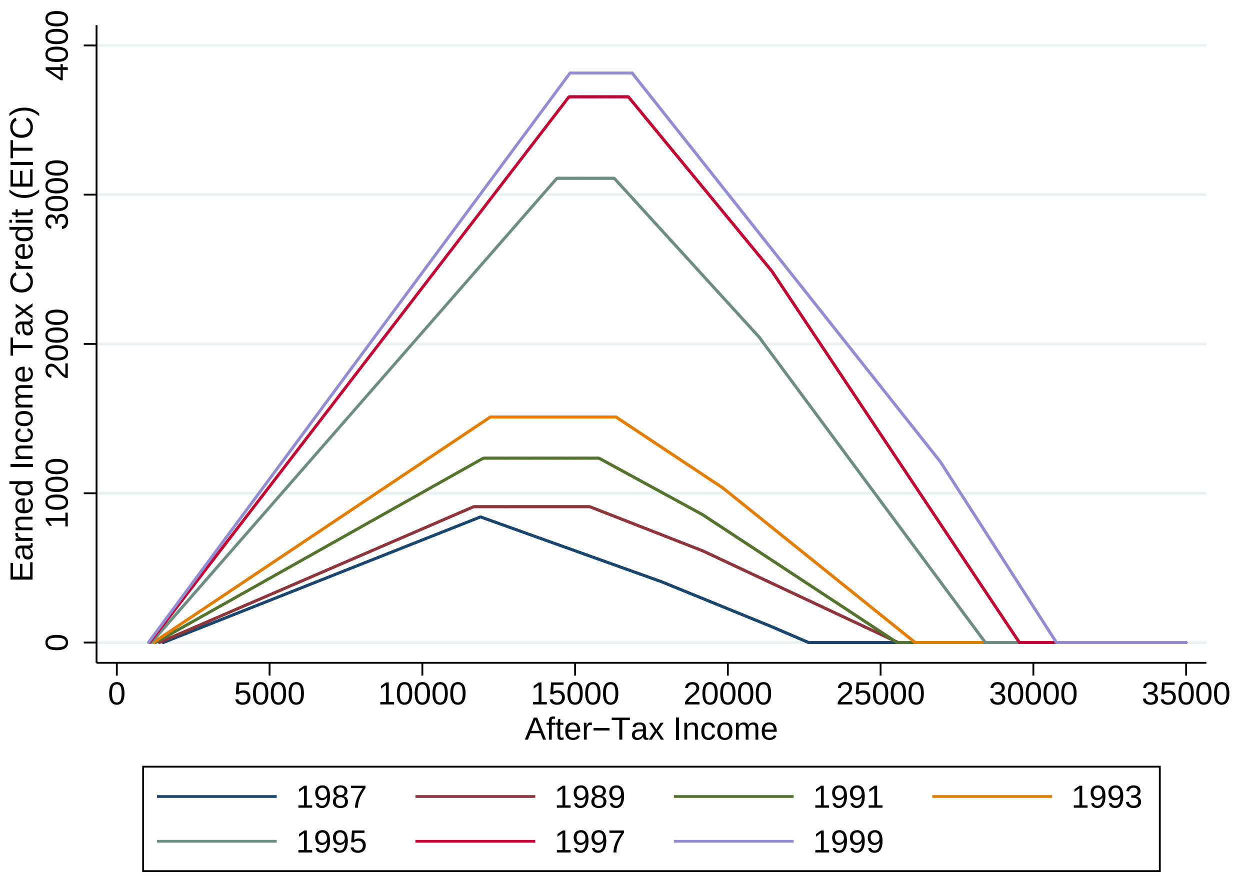
Panel A: Average PIAT Score



Panel B: Average BPI Score

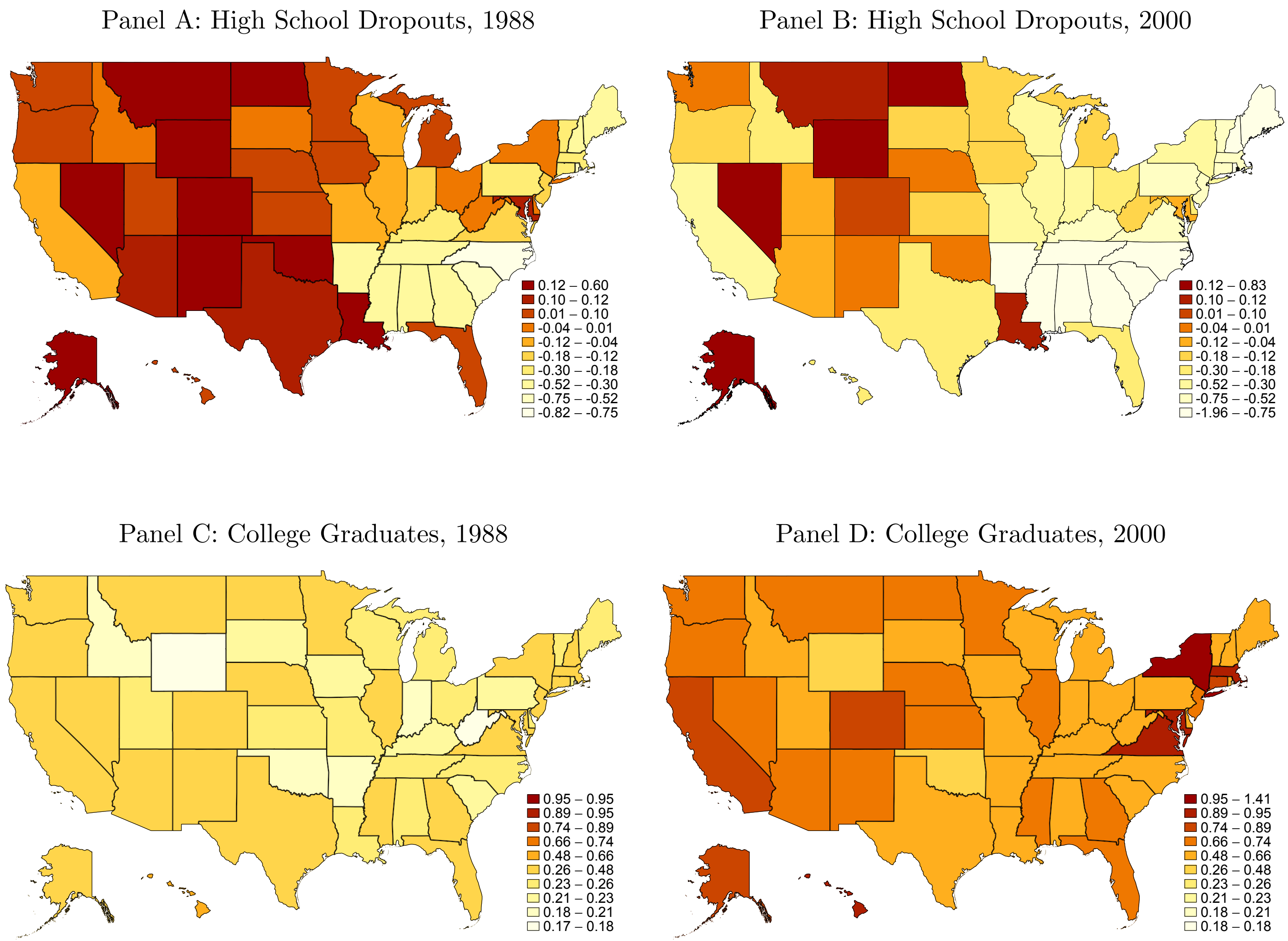
Notes: This figure shows the average cognitive and behavioral outcomes of children by after-tax family income deciles. For cognitive measures we consider the average standardized PIAT score between the math, reading recognition, and reading comprehension indexes. The behavioral measure is the average of the standardized Behavior Problems Index (BPI). The after-tax family income is calculated using the TAXSIM program. Source: C-NLSY.

Figure 2: The EITC Expansion



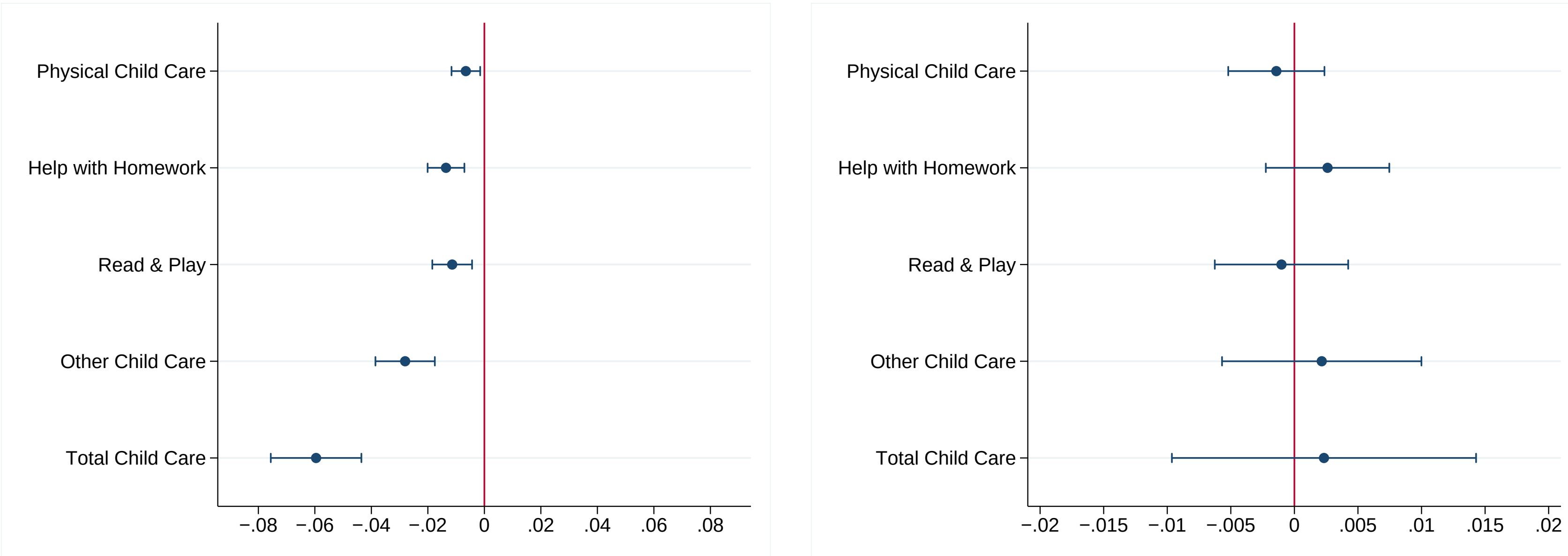
Notes: This figure shows the changes in the federal EITC schedule for families with two children. The after-tax family income is in real (2000) dollars. We calculate the EITC benefits over time using the TAXSIM program.

Figure 3: Labor Demand Shocks



Notes: This figure shows the variation in labor demand shocks between states and over time for less educated (school dropouts) and highly educated (college graduates) women. Panels A–B show the variation of labor demand shocks for the less educated group. Panels C–D show the variation of labor demand shocks for the highly educated group. Sources: CPS and Census 1980.

Figure 4: Time Allocated to Child Care, Mother's Hours Worked, and Family Income



Panel A: Child Care Activities and Mother's Hours Worked

Panel B: Child Care Activities and Family Income

Notes: This figure shows the effect of hours worked and family income on time (hours per week) allocated to child care activities. Panel A displays the regression coefficients (with a 95% confidence interval) for the effect of hours worked on each measure for time investment in child care activities. Panel B displays the regression coefficients (with a 95% confidence interval) for the effect of family income on each measure for time investment in child care activities. See text for further details. Sources: ATUS and AHTUS.

Figure 5: The Effect of Maternal Labor Supply on Child Achievement

Notes: This figure shows the causal effect of maternal hours worked on child achievement as a function of mothers' hourly wage rate (green line). The plotted values in the background show the empirical distributions of real hourly wages ($2000) for single and married mothers (top 5% excluded). The solid line represents the overall effect of maternal labor supply (income and substitution effects) based on our baseline results in Table 3, column (2).

Table 1: Summary Statistics

	Combined Math-Reading		Behavior Problems Index	
	Mean (1)	St.Dev. (2)	Mean (3)	St.Dev. (4)
Math	43.62	13.55	40.54	15.28
Reading recognition	47.29	16.05	43.98	17.57
Reading comprehension	42.60	13.70	40.02	14.97
Behavior Problems Index	3.22	1.13	3.23	1.13
Antisocial	4.49	1.59	4.50	1.59
Anxious	3.29	1.47	3.32	1.47
Headstrong	2.64	1.67	2.64	1.67
Hyperactive	3.23	1.60	3.20	1.60
Peer conflicts	2.49	0.84	2.49	0.84
Family income	37,775	30,132	38,463	30,701
Hours worked (Y)	1,258	986	1,234	982
Age	10.69	2.31	10.11	2.57
Male	0.50	0.50	0.50	0.50
White	0.46	0.50	0.48	0.50
Black	0.34	0.47	0.32	0.47
Hispanic	0.20	0.40	0.20	0.40
No siblings	0.09	0.28	0.09	0.29
One sibling	0.37	0.48	0.38	0.49
Two or more siblings	0.54	0.50	0.53	0.50
Mother's marital status:				
Married	0.63	0.48	0.65	0.48
Mother's education:				
High school dropout	0.22	0.41	0.21	0.40
High school graduate	0.49	0.50	0.50	0.50
Some college	0.21	0.41	0.21	0.41
Graduated college	0.08	0.27	0.08	0.28
Observations	12,288		13,777	

Notes: This table shows the summary statistics of our estimating samples. Columns (1) and (2) refer to the estimating sample for the analysis of child cognitive development (combined Math-Reading test score). Columns (3) and (4) consider the estimating sample for the analysis of child behavioral development (Behavior Problems Index, BPI). Income is after-tax income and it is measured in year 2000 dollars. Hours worked are yearly hours. Source: C-NLSY

Table 2: First Stage Estimates

	Combined Math-Reading		Behavior Problems Index	
	ΔIncome (1)	ΔHours Worked (2)	ΔIncome (3)	ΔHours Worked (4)
ΔEITC	1.026**	1.481***	1.101**	1.488***
	(0.488)	(0.282)	(0.482)	(0.280)
LabDemShocks	1.659***	0.322*	2.067***	0.245
	(0.395)	(0.186)	(0.405)	(0.178)
SW Chi-sq. (Under id)	13.21	14.40	21.89	20.57
P-value	0.00	0.00	0.00	0.00
SW F (Weak id)	13.19	14.38	21.86	20.54
P-value	0.00	0.00	0.00	0.00
KP (Weak id)	6.42	6.42	10.43	10.43
Observations	12,288	12,288	13,777	13,777

Notes: This table shows the estimates for both our first stage models. Dependent variable: ΔIncome (columns 1 and 3), and ΔHours worked (columns 2 and 4). Columns (1) and (2) refer to the estimating sample for the analysis of child cognitive development (combined Math-Reading test score). Columns (3) and (4) consider the estimating sample for the analysis of child behavioral development (Behavior Problems Index, BPI). For each analysis, the two endogenous variables are: changes in income (ΔIncome) and changes in maternal hours worked (ΔHours). The two instrumental variables are: changes in EITC benefits (ΔEITC) and labor demand shocks (*LabDemShocks*). Income and the EITC are measured in $1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. All models include a third order Taylor polynomial expansion of predicted income as a control function (see equation 7). All models also include controls for child's age, gender, race, and number of siblings. Standard errors are clustered at the family level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 3: Income, Hours Worked, and Child Test Scores

	Combined Math-Reading	
	OLS (1)	IV (2)
ΔIncome	0.001*	0.044***
	(0.000)	(0.015)
ΔHours worked	0.000	-0.060**
	(0.001)	(0.024)
Observations	12,288	12,288

Notes: This table shows the estimates for our analysis of child cognitive development. Dependent variable: Combined Math-Reading test score. Column (1) reports the OLS estimates. Column (2) shows the IV estimates. The two instrumental variables are: changes in EITC benefits (ΔEITC) and labor demand shocks ($LabDemShocks$). Income is measured in $1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. All models include a third order Taylor polynomial expansion of predicted income as a control function (see equation 7). All models also include controls for child's age, gender, race, and number of siblings. Standard errors are clustered at the family level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 4: Income, Hours Worked, and Child Behavior

	Behavior Problems Index	
	OLS	IV
	(1)	(2)
ΔIncome	0.000	0.013
	(0.000)	(0.009)
ΔHours worked	-0.001	-0.052**
	(0.001)	(0.022)
Observations	13,777	13,777

Notes: This table shows the estimates for our analysis of child behavioral development. Dependent variable: Behavior Problems Index (BPI). Column (1) reports the OLS estimates. Column (2) shows the IV estimates. The two instrumental variables are: changes in EITC benefits (ΔEITC) and labor demand shocks ($LabDemShocks$). Income is measured in $1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. All models include a third order Taylor polynomial expansion of predicted income as a control function (see equation 7). All models also include controls for child's age, gender, race, and number of siblings. Standard errors are clustered at the family level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 5: The Effect of Family Income and Hours Worked in Isolation

	Combined Math-Reading			Behavior Problems Index		
	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)
ΔIncome	0.017**		0.044***	-0.003		0.013
	(0.007)		(0.015)	(0.007)		(0.009)
ΔHours worked		-0.021*	-0.060**		-0.040**	-0.052**
		(0.011)	(0.024)		(0.018)	(0.022)
First Stage Tests (Income/Hours):						
SW Chi-sq. (Under id)	19.37	29.19	13.21/14.40	27.68	29.09	21.89/20.57
P-value	0.00	0.00	0.00/0.00	0.00	0.00	0.00/0.00
SW F (Weak id)	9.67	14.57	13.19/14.38	13.82	14.53	21.86/20.54
P-value	0.00	0.00	0.00/0.00	0.00	0.00	0.00/0.00
KP (Weak id)	9.67	14.57	6.42	13.82	14.53	10.43
Observations	12,288	12,288	12,288	13,777	13,777	13,777

Notes: This table shows the estimates for our analysis of child cognitive development (columns 1–3) and child behavioral development (columns 4–6). Dependent variable: Combined Math-Reading test score (columns 1–3), and Behavior Problems Index (BPI) (columns 4–6). Columns (1) and (4) show the impact of family income in isolation. Columns (2) and (5) show the impact of maternal hours worked in isolation. Columns (3) and (6) show the contemporaneous impact of family income and maternal hours worked. All estimates are IV estimates. For comparison purposes, the coefficient for the effect of family income estimated in Dahl and Lochner (2017) is equal to 0.041. See their work for further details. In columns (1) to (6), the two instrumental variables are: changes in EITC benefits (ΔEITC) and labor demand shocks (*LabDemShocks*). Income is measured in $1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. All models in columns (1) to (6) include a third order Taylor polynomial expansion of predicted income as a control function (see equation 7). The same models also include controls for child's age, gender, race, and number of siblings. Standard errors are clustered at the family level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 6: Heterogeneous Effect of EITC Changes: Mother's Employment

	Combined Math-Reading IV (1)	Behavior Problems Index IV (2)
ΔIncome	0.032***	0.002
	(0.009)	(0.008)
ΔHours worked	-0.039***	-0.028**
	(0.011)	(0.013)
First Stage Coefficients:		
ΔIncome:		
ΔEITC*Employed$_{(t-1)}$	1.557**	1.744***
	(0.640)	(0.638)
ΔEITC*Non-Employed$_{(t-1)}$	0.637	0.614
	(0.504)	(0.512)
LabDemShocks	1.613***	2.009***
	(0.395)	(0.404)
ΔHours worked:		
ΔEITC*Employed$_{(t-1)}$	0.544	0.553
	(0.365)	(0.355)
ΔEITC*Non-Employed$_{(t-1)}$	2.166***	2.194***
	(0.294)	(0.298)
LabDemShocks	0.403**	0.330*
	(0.189)	(0.181)
First Stage Tests (Income/Hours):		
SW Chi-sq. (Under id)	21.47/62.24	30.61/63.37
P-value	0.00/0.00	0.00/0.00
SW F (Weak id)	10.71/31.07	15.28/31.64
P-value	0.00/0.00	0.00/0.00
KP (Weak id)	7.06	10.05
Observations	12,288	13,777

Notes: This table shows the IV estimates for our robustness analysis. Dependent variable: Combined Math-Reading test score (column 1), and Behavior Problems Index (BPI) (column 2). First stage estimates are obtained by interacting the EITC instrument with the mother's lagged employment status. Income is measured in $1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. All models include a third order Taylor polynomial expansion of predicted income as a control function (see equation 7). All models also include controls for child's age, gender, race, and number of siblings. Standard errors are clustered at the family level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 7: Single Test Scores

	Math IV (1)	Reading Recognition IV (2)	Reading Comprehension IV (3)
ΔIncome	0.029**	0.055***	0.030**
	(0.012)	(0.018)	(0.013)
ΔHours worked	-0.036*	-0.070**	-0.049**
	(0.021)	(0.029)	(0.022)
Observations	12,288	12,288	12,288

Notes: This table shows the IV estimates for each single PIAT test score. Dependent variable: Math test score (column 1), Reading Recognition test score (column 2), and Reading Comprehension test score (column 3). The two instrumental variables are: changes in EITC benefits (ΔEITC) and labor demand shocks ($LabDemShocks$). Income is measured in $1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. All models include a third order Taylor polynomial expansion of predicted income as a control function (see equation 7). All models also include controls for child's age, gender, race, and number of siblings. Standard errors are clustered at the family level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 8: Single Behavior Problems Index

	Antisocial IV (1)	Anxious IV (2)	Headstrong IV (3)	Hyperactive IV (4)	Peer Conflicts IV (5)
ΔIncome	0.012	-0.007	0.015	0.020**	0.009
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)
ΔHours worked	-0.048**	-0.027	-0.046**	-0.036*	-0.041*
	(0.022)	(0.019)	(0.021)	(0.021)	(0.025)
Observations	13,777	13,777	13,777	13,777	13,777

Notes: This table shows the IV estimates for each single BPI score. Dependent variable: Antisocial behavior (column 1), Anxious behavior (column 2), Headstrong behavior (column 3), Hyperactive behavior (column 4), and Peer Conflicts behavior (column 5). The two instrumental variables are: changes in EITC benefits (ΔEITC) and labor demand shocks ($LabDemShocks$). Income is measured in $1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. All models include a third order Taylor polynomial expansion of predicted income as a control function (see equation 7). All models also include controls for child's age, gender, race, and number of siblings. Standard errors are clustered at the family level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 9: Income, Hours Worked, and Early Childhood Development

	Compliance IV (1)	Insecure Attachment IV (2)	Compliance and Ins.Attach. IV (3)	Sociability IV (4)
ΔIncome	0.046	0.020	0.046	0.011
	(0.031)	(0.022)	(0.029)	(0.020)
ΔHours worked	-0.039	-0.044	-0.053	-0.010
	(0.043)	(0.034)	(0.039)	(0.045)
Age range	1–7	1–7	1–7	2–7
Observations	4,807	4,884	4,656	2,969

Notes: This table shows the IV estimates for our analysis of early childhood temperament development. Dependent variable: Compliance score (column 1), Insecure Attachment score (column 2), Combined Compliance and Insecure Attachment score (column 3), and Sociability score (column 4). The two instrumental variables are: changes in EITC benefits (ΔEITC) and labor demand shocks (*LabDemShocks*). Income is measured in $1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. All models include a third order Taylor polynomial expansion of predicted income as a control function (see equation 7). All models also include controls for child's age, gender, race, and number of siblings. Standard errors are clustered at the family level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 10: Heterogeneous Effects: Mother Characteristics

	Combined Math-Reading IV (1)	Behavior Problems Index IV (2)
	Panel A: Mother's Education	
ΔIncome*HS or less	0.031**	0.012
	(0.015)	(0.010)
ΔIncome*Some college or more	0.030**	0.013
	(0.016)	(0.011)
ΔHours worked*HS or less	**-0.058****	**-0.054****
	(0.024)	(0.021)
ΔHours worked*Some college or more	**0.001**	**-0.049****
	(0.028)	(0.024)
Observations	12,288	13,777
	Panel B: Mother's AFQT	
ΔIncome*Low AFQT	0.030**	0.016
	(0.015)	(0.010)
ΔIncome*High AFQT	0.033**	0.018*
	(0.016)	(0.010)
ΔHours worked*Low AFQT	**-0.064****	**-0.052****
	(0.025)	(0.022)
ΔHours worked*High AFQT	**0.001**	**-0.073*****
	(0.028)	(0.023)
Observations	11,939	13,348
	Panel C: Mother's Marital Status	
ΔIncome*Married	0.038**	0.016
	(0.016)	(0.010)
ΔIncome*Unmarried	0.044***	0.013
	(0.017)	(0.011)
ΔHours worked*Married	**-0.010**	**-0.065****
	(0.030)	(0.029)
ΔHours worked*Unmarried	**-0.069****	**-0.052****
	(0.028)	(0.022)
Observations	12,288	13,777

Notes: This table shows the IV heterogeneous effects of income and maternal hours worked on child development. Dependent variable: Combined Math-Reading test score (column 1), and Behavior Problems Index (BPI) (column 2). We divide mothers according to: (i) Panel A: educational attainments (high school (HS) diploma or less vs. some college or more); (ii) Panel B: AFTQ score (below or above the median); and (iii) Panel C: marital status (married vs. unmarried). The two instrumental variables are: changes in EITC benefits (ΔEITC) and labor demand shocks ($LabDemShocks$). Income is measured in $1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. All models include a third order Taylor polynomial expansion of predicted income as a control function (see equation 7). All models also include controls for child's age, gender, race, and number of siblings. Standard errors are obtained through a family-level clustered bootstrap procedure based on 100 repetitions and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 11: Heterogeneous Effects: Child Characteristics

	Combined Math-Reading IV (1)	Behavior Problems Index IV (2)
	Panel A: Child's Race	
ΔIncome*Black or Hispanic	0.046**	0.014
	(0.018)	(0.009)
ΔIncome*White	0.047**	0.015
	(0.019)	(0.010)
ΔHours worked*Black or Hispanic	**-0.069****	**-0.050****
	(0.031)	(0.023)
ΔHours worked*White	**-0.047**	**-0.068*****
	(0.032)	(0.022)
Observations	12,288	13,777
	Panel B: Child's Age	
ΔIncome*Below 12	0.048**	0.012
	(0.019)	(0.009)
ΔIncome*Above 12	0.049**	0.015
	(0.020)	(0.010)
ΔHours worked*Below 12	**-0.076****	**-0.055****
	(0.031)	(0.023)
ΔHours worked*Above 12	**-0.053**	**-0.055****
	(0.033)	(0.022)
Observations	12,288	13,777

Notes: This table shows the IV heterogeneous effects of income and maternal hours worked on child development. Dependent variable: Combined Math-Reading test score (column 1), and Behavior Problems Index (BPI) (column 2). We divide children according to: (i) Panel A: race (white vs. black or Hispanic); and (ii) Panel B: age (below 12 years old vs. above 12 years old). The two instrumental variables are: changes in EITC benefits (ΔEITC) and labor demand shocks ($LabDemShocks$). Income is measured in $1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. All models include a third order Taylor polynomial expansion of predicted income as a control function (see equation 7). All models also include controls for child's age, gender, race, and number of siblings. Standard errors are obtained through a family-level clustered bootstrap procedure based on 100 repetitions and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table 12: Maternal Employment Status, Investment in the Child, and Child's Activities

	(LI,NE) (1)	(LI,E) (2)	(HI,NE) (3)	(HI,E) (4)	(LI,E)-(LI,NE) (5)	p-val (6)	(HI,E)-(HI,NE) (7)	p-val (8)
	Panel A: Parenting							
Encourage hobbies	0.92	0.91	0.96	0.94	-0.01	0.64	-0.01	0.38
Phys. affection (times past week)	8.43	9.51	15.55	13.98	1.07	0.16	-1.57	0.36
Parenting class pre-birth	0.15	0.14	0.20	0.18	-0.02	0.36	-0.03	0.18
Parenting class	0.24	0.20	0.31	0.26	-0.04	0.06	-0.05	0.03
Never cared by others	0.57	0.24	0.45	0.15	-0.33	0.00	-0.30	0.00
Use of rules	0.58	0.51	0.54	0.50	-0.07	0.02	-0.04	0.19
Control who the child is with	0.55	0.58	0.59	0.47	0.03	0.32	-0.11	0.00
Control activities after school	0.60	0.66	0.70	0.57	0.06	0.08	-0.13	0.00
Set homework time	0.70	0.78	0.82	0.72	0.08	0.01	-0.10	0.00
	Panel B: Reaction to Poor Scholastic Performance							
Contact faculty ($\geq$ 6 y.o.)	0.84	0.82	0.81	0.88	-0.02	0.47	0.07	0.01
Closer eye on activities	0.84	0.84	0.89	0.88	0.00	0.84	-0.01	0.80
Lecture a child	0.80	0.81	0.74	0.80	0.01	0.80	0.06	0.04
Tell child to work harder	0.81	0.80	0.66	0.73	-0.01	0.84	0.07	0.04
Help with schoolwork	0.80	0.82	0.75	0.76	0.02	0.39	0.01	0.78
	Panel C: Family Environment Scales							
Full home	17.39	18.10	19.90	20.18	0.71	0.00	0.28	0.13
Cognitive stimulation	8.67	9.24	10.04	10.13	0.57	0.00	0.09	0.44
Emotional support	8.72	8.86	9.86	10.05	0.15	0.14	0.19	0.09
Parental warmth	4.46	4.47	4.59	4.48	0.01	0.67	-0.11	0.00
	Panel D: Time Diaries (in seconds per day)							
School	12,161	16,323	12,745	16,743	4,162	0.00	3,998	0.00
TV	6,492	6,271	5,769	5,247	-221	0.49	-522	0.12
Electronic games	365	538	335	361	172	0.10	27	0.73
Art, sculpture	242	123	244	214	-119	0.01	-30	0.56
Books	248	238	350	337	-10	0.83	-13	0.81
Books ($\geq$ 4 y.o.)	280	248	332	334	-32	0.59	2	0.97
Visiting others, socializing	409	526	261	288	117	0.40	28	0.76

Notes: This table shows several measures for investment in the child development process using the CDS supplement of the PSID data set. All measures refer to children aged 0–12 in 1997. LI means low family income (below $35,000), HI means high family income (above $35,000). NE means that the mother is non-employed in 1997, E means that the mother is employed in 1997. All the variables (if not differently specified) excepted time diaries are indicator variables. Time diaries variables (Panel D) are expressed in seconds per day and refer to weekdays only.

Appendix A: Additional Tables

Table A.1: First Stage Estimates – Full Set of Individual Controls

	Combined Math-Reading		Behavior Problems Index	
	ΔIncome (1)	ΔHours Worked (2)	ΔIncome (3)	ΔHours Worked (4)
ΔEITC	1.026**	1.481***	1.101**	1.488***
	(0.488)	(0.282)	(0.482)	(0.280)
LabDemShocks	1.659***	0.322*	2.067***	0.245
	(0.395)	(0.186)	(0.405)	(0.178)
Male	0.185	-0.006	0.134	-0.012
	(0.279)	(0.119)	(0.288)	(0.110)
Age	-0.155**	-0.007	-0.109**	-0.020
	(0.064)	(0.028)	(0.052)	(0.024)
No siblings	0.053	0.024	-0.181	0.045
	(0.533)	(0.240)	(0.481)	(0.212)
Two or more sibling	0.079	-0.070	0.128	0.021
	(0.397)	(0.163)	(0.406)	(0.152)
Black	-2.728***	-0.441**	-2.624***	-0.393**
	(0.447)	(0.180)	(0.417)	(0.171)
Hispanic	-2.087***	-0.342*	-1.782***	-0.312*
	(0.525)	(0.205)	(0.522)	(0.189)
SW Chi-sq. (Under id)	13.21	14.40	21.89	20.57
P-value	0.00	0.00	0.00	0.00
SW F (Weak id)	13.19	14.38	21.86	20.54
P-value	0.00	0.00	0.00	0.00
KP (Weak id)	6.42	6.42	10.43	10.43
Observations	12,288	12,288	13,777	13,777

Notes: This table shows the estimates for both our first stage models. Dependent variable: Δ Income (columns 1 and 3), and ΔHours worked (columns 2 and 4). Columns (1) and (2) refer to the estimating sample used for the analysis of child cognitive development (combined Math-Reading test score). Columns (3) and (4) consider the estimating sample used for the analysis of child behavioral development (Behavior Problems Index, BPI). For each analysis, the two endogenous variables are: changes in income (ΔIncome) and changes in maternal hours worked (ΔHours). The two instrumental variables are: changes in EITC benefits (ΔEITC) and labor demand shocks ($LabDemShocks$). Income and the EITC are measured in $1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. All models include a third order Taylor polynomial expansion of predicted income as a control function (see equation 7). One sibling is the reference category for child's number of siblings. White is the reference category for child's race. Standard errors are clustered at the family level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.2: Changes in EITC Schedule, Labor Demand Shocks, and Spouse Labor Supply

	Combined Math-Reading	Behavior Problems Index
	ΔHours Worked Spouse (1)	ΔHours Worked Spouse (2)
ΔEITC	0.402	0.788
	(0.661)	(0.644)
LabDemShocks	0.166	0.098
	(0.204)	(0.192)
Observations	7,726	8,845

Notes: This table shows the estimates for our analysis of changes in spouse labor supply. Dependent variable: ΔHours worked by the spouse. Column (1) refers to the estimating sample used for the analysis of child cognitive development (combined Math-Reading test score). Column (2) considers the estimating sample used for the analysis of child behavioral development (Behavior Problems Index, BPI). The two instrumental variables are: changes in EITC benefits (ΔEITC) and labor demand shocks ($LabDemShocks$). Income and the EITC are measured in $1,000 of year 2000 dollars. Hours worked by the spouse are yearly hours and expressed in hundreds. All models include a third order Taylor polynomial expansion of predicted income as a control function (see equation 7). All models also include controls for child's age, gender, race, and number of siblings. Standard errors are clustered at the family level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.3: Income, Hours Worked, and Child Test Scores – Full Set of Individual Controls

	Combined Math-Reading	
	OLS	IV
	(1)	(2)
ΔIncome	0.001*	0.044***
	(0.000)	(0.015)
ΔHours worked	0.000	-0.060**
	(0.001)	(0.024)
Male	0.024**	0.017
	(0.010)	(0.017)
Age	0.001	0.008*
	(0.003)	(0.005)
No siblings	-0.001	-0.006
	(0.020)	(0.032)
Two or more sibling	-0.026**	-0.028
	(0.012)	(0.022)
Black	-0.156***	-0.057
	(0.014)	(0.041)
Hispanic	-0.076***	-0.009
	(0.016)	(0.035)
Observations	12,288	12,288

Notes: This table shows the estimates for our analysis of child cognitive development. Dependent variable: Combined Math-Reading test score. Column (1) reports the OLS estimates. Column (2) shows the IV estimates. The two instrumental variables are: changes in EITC benefits (ΔEITC) and labor demand shocks (*LabDemShocks*). Income is measured in $1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. All models include a third order Taylor polynomial expansion of predicted income as a control function (see equation 7). One sibling is the reference category for child's number of siblings. White is the reference category for child's race. Standard errors are clustered at the family level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.4: Income, Hours Worked, and Child Behavior – Full Set of Individual Controls

	Behavior Problems Index	
	OLS	IV
	(1)	(2)
ΔIncome	0.000	0.013
	(0.000)	(0.009)
ΔHours worked	-0.001	-0.052**
	(0.001)	(0.022)
Male	-0.016	-0.018
	(0.011)	(0.013)
Age	0.010***	0.011***
	(0.003)	(0.003)
No siblings	0.026	0.027
	(0.020)	(0.023)
Two or more sibling	0.002	0.005
	(0.013)	(0.015)
Black	-0.008	0.010
	(0.015)	(0.028)
Hispanic	0.023	0.031
	(0.016)	(0.022)
Observations	13,777	13,777

Notes: This table shows the estimates for our analysis of child behavioral development. Dependent variable: Behavior Problems Index (BPI). Column (1) reports the OLS estimates. Column (2) shows the IV estimates. The two instrumental variables are: changes in EITC benefits (ΔEITC) and labor demand shocks ($LabDemShocks$). Income is measured in $1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. All models include a third order Taylor polynomial expansion of predicted income as a control function (see equation 7). One sibling is the reference category for child's number of siblings. White is the reference category for child's race. Standard errors are clustered at the family level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.5: Baseline Estimates with State Trends

	Combined Math-Reading		Behavior Problems Index	
	OLS (1)	IV (2)	OLS (3)	IV (4)
ΔIncome	0.001*	0.041***	0.000	0.008
	(0.000)	(0.010)	(0.000)	(0.006)
ΔHours worked	0.000	-0.056**	-0.001	-0.049**
	(0.001)	(0.022)	(0.001)	(0.020)
First Stage Tests (Income/Hours):				
SW Chi-sq. (Under id)		23.54/19.32		40.98/25.72
P-value		0.00/0.00		0.00/0.00
SW F (Weak id)		23.41/19.21		40.77/25.60
P-value		0.00/0.00		0.00/0.00
KP (Weak id)		10.30		15.38
Observations	12,288	12,288	13,777	13,777

Notes: This table shows the estimates for the analysis of cognitive and behavioral development with a state fixed effects specification. Dependent variable: Combined Math-Reading test score (columns 1–2), and Behavior Problems Index (BPI) (columns 3–4). Income and EITC are measured in $1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. All models include state fixed effects and a third order Taylor polynomial expansion of predicted income as a control function (see equation 7). All models also include state fixed effects, as well as controls for child's age, gender, race, and number of siblings. Standard errors are clustered at the family level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.6: Baseline Estimates with Controls for School Financial and Economic Resources

	Combined Math-Reading		Behavior Problems Index	
	OLS (1)	IV (2)	OLS (3)	IV (4)
ΔIncome	0.001*	0.042***	0.000	0.012
	(0.000)	(0.014)	(0.000)	(0.009)
ΔHours worked	0.000	-0.057**	-0.001	-0.051**
	(0.001)	(0.023)	(0.001)	(0.022)
ΔTotal revenues (per pupil)	0.003	-0.002	0.002	0.006
	(0.012)	(0.020)	(0.013)	(0.015)
ΔTotal public expenditure (per pupil)	0.012	-0.016	0.021	-0.006
	(0.022)	(0.044)	(0.023)	(0.032)
First Stage Tests (Income/Hours):				
SW Chi-sq. (Under id)		14.58/15.60		23.45/21.03
P-value		0.00/0.00		0.00/0.00
SW F (Weak id)		14.56/15.58		23.41/21.00
P-value		0.00/0.00		0.00/0.00
KP (Weak id)		7.08		11.05
Observations	12,255	12,255	13,735	13,735

Notes: This table shows the estimates for the analysis of cognitive and behavioral development when we control for per-pupil school resources by state. Dependent variable: Combined Math-Reading test score (columns 1–2), and Behavior Problems Index (BPI) (columns 3–4). Family income, the EITC, the total revenues per pupil, and the total expenditure per pupil are measured in $1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. The total revenues per pupil are the total revenues from all sources divided by the fall membership as reported in the state finance file. The total current expenditure per pupil is the total current expenditure for public elementary and secondary education divided by the fall membership as reported in the state financial file. Data about revenues and expenditures are from the CDD National Public Education Financial Survey. All models also include controls for child's age, gender, race, and number of siblings. Standard errors are clustered at the family level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.7: Common Pre-trends between Labor Demand Shocks and Child Development

	Combined Math-Reading (1)	Behavior Problems Index (2)
LabDemShocks $(t+1)$		
F-stat.	6.11	0.12
P-value	0.01	0.73
LabDemShocks $(t+2)$		
F-stat.	0.70	0.38
P-value	0.40	0.54
LabDemShocks $(t+3)$		
F-stat.	1.35	0.61
P-value	0.25	0.43
LabDemShocks $(t+1)$,$(t+2)$		
F-stat.	0.47	0.23
P-value	0.63	0.80
LabDemShocks $(t+1)$,$(t+2)$,$(t+3)$		
F-stat.	0.81	1.50
P-value	0.49	0.21

Notes: This table is based on the analysis of the effect of future labor demand shocks on current cognitive and behavioral development. The table shows the F-statistic and the relative significance of the coefficients for future labor demand shocks. In cases with multiple variables for future labor demand shocks, we jointly test the significance of labor demand shocks. Dependent variable: Combined Math-Reading test score (column 1), and Behavior Problems Index (BPI) (column 3). Each specification contains controls for EITC benefits (ΔEITC) and labor demand shocks ($LabDemShocks$). In addition, each model also contains variables for future labor demand shocks as explained in each panel header. All models include a third order Taylor polynomial expansion of predicted income as a control function (see equation 7). All models also include controls for child's age, gender, race, and number of siblings. Standard errors are clustered at the family level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.8: Baseline Estimates Excluding Movers Across States

	Combined Math-Reading		Behavior Problems Index	
	OLS (1)	IV (2)	OLS (3)	IV (4)
ΔIncome	0.001**	0.052***	0.000	0.010
	(0.000)	(0.020)	(0.000)	(0.010)
ΔHours worked	0.000	-0.069**	-0.000	-0.053**
	(0.001)	(0.030)	(0.001)	(0.024)
Observations	11,707	11,707	13,087	13,087

Notes: This table shows the estimates for the analysis of cognitive and behavioral development once we exclude observations with changes in state of residence in two consecutive periods. Dependent variable: Combined Math-Reading test score (columns 1–2), and Behavior Problems Index (BPI) (columns 3–4). Income and EITC are measured in $1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. All models include a third order Taylor polynomial expansion of predicted income as a control function (see equation 7). All models also include controls for child's age, gender, race, and number of siblings. Standard errors are clustered at the family level and reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Table A.9: Time Allocation to Child Care, Mother's Hours Worked, and Family Income

	Physical Child Care (1)	Help with Homework (2)	Read & Play (3)	Other Child Care (4)	Total Child Care (5)
Income	-0.001	0.003	-0.001	0.002	0.002
	(0.002)	(0.002)	(0.003)	(0.004)	(0.006)
Hours worked (per week)	-0.007**	-0.014***	-0.011***	-0.028***	-0.060***
	(0.003)	(0.003)	(0.004)	(0.005)	(0.008)
Observations	3,183	3,183	3,183	3,183	3,183

Notes: This table shows the OLS estimates for the analysis of parental time investment in the child using data from the American Time Use Survey (ATUS) and the American Heritage Time Use Survey (AHTUS). Dependent variable: Physical Child Care (column 1), Help with Homework (column 2), Read and Play (column 3), Other Child Care (column 4), and Total Child Care (column 5). Time investment is measured in hours per week. Income is measured in $1,000 of year 2003 dollars. Hours worked are weekly hours worked. All models include controls for single-head household, mother's age, child's age, mother's education, number of siblings. All models also include year fixed effects. Standard errors are in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% level, respectively.

Appendix B: Additional Material

B.1 The Child Development Supplement

In Table B.1 we show the variables construction process used to analyze the Child Development Supplement (CDS). We focus on the first wave of the CDS, the so-called CDS-I, collected in 1997.

Table B.1: CDS – Variables Construction

	Original Definition (1)	Original Answers (2)	Variable Definition (3)
Encourage hobbies	Family encourages hobbies	Yes, No	Yes=1
Physical affection	Shown physical affection (times past week)	1-350	1-350
Parenting class pre-birth	Take parenting classes before child's birth	Yes, No	Yes=1
Parenting class	Never take parenting classes	Yes, No	No=1
Never cared by others	Child's age when first cared by others	0-10	Never=1
Use of rules	Family with lots of rules or not very many rules	Lots, Not many	Lots=1
How often...			
Control who the child is with	Control which children your child spend time with	N, S, SM, O, VO	O, VO=1
Control activities after school	Control how child spends time after school	N, S, SM, O, VO	O, VO=1
Set homework time	Set a time for homework	N, S, SM, O, VO	O, VO=1
Reaction to grades lower than expected:			
Contact faculty	Contact teacher/principal	U, SU, NS, SL, L	SL, L=1
Closer eye on activities	Closer eye on child's activities	U, SU, NS, SL, L	L=1
Lecture a child	Lecture the child	U, SU, NS, SL, L	SL, L=1
Tell child to work harder	Tell the child to spend more time on homework	U, SU, NS, SL, L	L=1
Help with schoolwork	Increase time helping the child with schoolwork	U, SU, NS, SL, L	L=1
Full home	Full home scale	7-27	7-27
Cognitive stimulation	Cognitive stimulation subscale	2-14	2-14
Emotional support	Emotional support subscale	2-14	2-14
Parental warmth	Parental warmth subscale	1-5	1-5
Time diaries (in seconds)			
School	Student, attending classes	0-86,400	0-86,400
TV	TV use	0-86,400	0-86,400
Electronic games	Electronic video games use	0-86,400	0-86,400
Art, sculpture	Art, arts and crafts,	0-86,400	0-86,400
Books	Reading or looking at books	0-86,400	0-86,400
Visiting others, socializing	Socializing with people outside own household	0-86,400	0-86,400

Note: This table shows variable definitions from the CDS-I data set used in Section 5.4. In the table the following abbreviations are used: (i) N: Never, S: Seldom, SM: Sometimes, O: Often, VO: Very often; (ii) U: Not at all likely, SU: Somewhat unlikely, NS: Not sure how likely, SL: Somewhat likely, L: likely. Refer to the text and the CDS-I User Guide Supplement for further details about the original and the constructed variables.