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

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Families face a trade-off when deciding how to allocate time between working and parenting. This decision can impact child development. In this paper, we study the effect of family income and maternal hours worked on child development. We exploit the longitudinal variation in the Earned Income Tax Credit benefits and in shocks on local labor market conditions as instruments to overcome the endogeneity of income and hours worked. We find evidence of a trade-off between the *income* effect (a surge in economic resources) and the *substitution* effect (less parental time) on child 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 cognitive and behavioral development by approximately 6 percent of a standard deviation. We find that the substitution effect dominates the income effect when the hourly wage is below $13.50.

Keywords: Child development; Family income; Maternal labor supply

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1 Introduction

Families face a trade-off when allocating their time and resources to child development. Working more hours generates higher earnings, but it comes at the cost of time spent with the child. Conversely, time spent at home includes an opportunity cost in terms of foregone earnings and consequent reduction in consumption and expenditures on goods for the child. Although both time and money are important for child development, the net effect on children from a surge in earnings that accompany a parent's increased work hours is unclear.

Support programs such as the Earned Income Tax Credit (EITC), one of the largest federal income support programs in the United States, provide income transfers on the condition that the recipient works. Mothers, and especially single mothers, are usually the main target of similar welfare programs and are most responsive to incentives (Meyer, 2002; Blundell and Hoynes, 2004; Blundell et al., 2016; Løken et al., 2018).[1] Such responsiveness might shape child development by introducing a trade-off between the *income* effect, which arises due to a surge in family income, and the *substitution* effect, which is due to maternal labor supply responses and a decrease in time parents spend with their child.

In this paper, we study the trade-off between the income and the substitution effects by looking at the contemporaneous impact of family income and maternal labor supply on cognitive and behavioral development of children aged 4–16. Our analysis is based on the National Longitudinal Study of Youth 1979 (NLSY79) data set matched with its Children (NLSY79-C) section. This data set covers a representative sample of the U.S. population in 1979 and provides longitudinal information about child development, family income, and hours worked by the mother and allows us to account for family-specific unobserved heterogeneity. We proxy cognitive development through the child's achievement on the Peabody Individual Achievement Test (PIAT) in mathematics and reading. To study behavioral development, we take advantage of the Behavior Problems Index (BPI).

[1] Hotz and Scholz (2003) and Nichols and Rothstein (2016) summarize theoretical and empirical findings about the effect of the EITC on maternal labor supply. Blundell et al. (2016) analyze the case of the United Kingdom and find substantial elasticities for women's labor supply.

Changes in family income and maternal labor supply are the results of individuals' choices. In order to identify the single causal effect of either family income or maternal labor supply on child development, we implement an instrumental variable (IV) identification strategy that builds upon the work by Dahl and Lochner (2012). In their work, the authors take advantage of quasi-experimental variation in the EITC to analyze the causal effect of family income on child achievement.[2] As the EITC is designed to incentivize individuals to work, we extend their framework by allowing the EITC to affect maternal labor supply.

Our IV strategy exploits two instrumental variables to correct the endogeneity of family income and maternal labor supply. The first instrument is based on the longitudinal changes in monetary benefits of the EITC. This variation provides us with exogenous changes in family resources available for allocation to children. At the same time, only working people are eligible for EITC benefits, which creates incentives for mothers to work. We construct the second instrument by using longitudinal shocks in local labor market demand. Shifts in local demand for labor affect equilibrium prices (wages) and, subsequently, family income and the equilibrium labor quantity.

The instrumental variable analysis suggests that an additional \$1,000 in family income improves cognitive development by 4.4 percent of a standard deviation.[3] The income effect on child cognitive development is counterbalanced by a negative effect of hours worked by the mother. An increase in maternal labor supply of 100 hours per year decreases child cognitive development by 6 percent of a standard deviation. We do not find a significant effect of family income on behavioral development, while the effect of maternal labor supply on behavioral development is similar to that for cognitive development.

We test the robustness of our findings by applying a new methodology that allows us to deal with the endogeneity of both family income and maternal labor supply with a single

[2] After the analysis by Lundstrom (2017), Dahl and Lochner (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.

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

instrumental variable. The methodology addresses concerns about the possibility that different instruments are characterized by different groups of compliers, and it is based on the use of the definition of family income as an extra source of identification. The definition of family income relates income with maternal labor supply: family income might indeed be defined as the sum of labor earnings plus other sources of income. The use of a single instrument such as the EITC combined with the relation between family income and maternal labor supply (income definition) allows us to overcome the need for a second instrument. Findings obtained with this new methodology are in line with our baseline estimates and confirm the existence of the trade-off between the income and the substitution effects on child development.

In the second part of the paper, we study the mechanism underlying the negative effect of maternal labor supply on child development. By using the time diary component of the American Time Use Survey (ATUS) we show, similar to Sayer et al. (2004), Guryan et al. (2008), and Fox et al. (2013), that working mothers invest less time in their children conditional on income. As a consequence, labor market conditions may shape the effect of labor supply on child development with the effect of maternal labor supply likely to depend on the wage the mother is paid. With higher earnings, mothers 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). According to our results, the substitution effect dominates the income effect when the after-tax hourly wage is below $13.50. The biggest fraction of mothers in our sample report wages below this threshold.

We further investigate the possible importance of alternative inputs in the child development process by analyzing heterogeneous effects of family income and maternal labor supply. We focus on dimensions such as mother's education, mother's skills, and marital status as possible sources of heterogeneity. Any evidence of heterogeneous income effects arise in our framework. 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 have access to better nonparental child care options. We do not find evidence of heterogeneous impacts of maternal labor supply on behavioral development.

One possible explanation for the heterogeneous effects of maternal labor supply is that maternal engagement in child rearing practices may differ by employment status and family income. Through the information contained in the Child Development Supplement (CDS) of the Panel Study of Income Dynamics (PSID), we highlight evidence of differential parental investments as a response to the maternal employment status when low-income families are compared to high-income families.

This article makes several key contributions to the existing literature on child development. First, we bridge the gap between the literature on the effect of family income and that on the effect of maternal labor supply on child development. Studies such as Duncan et al. (1998) and Blau (1999) have found evidence of the positive income effect on child achievements. The income effect on child development has been confirmed in instrumental variables settings such as Løken et al. (2012) and Dahl and Lochner (2012). Studies on the effect of maternal labor supply during childhood show, in general, that labor supply negatively affects child development (Baum, 2003; Ruhm, 2004; Bernal, 2008; Carneiro and Rodriguez, 2009; Bernal and Keane, 2011; Carneiro et al., 2015; Del Bono et al., 2016; Løken et al., 2018).

In light of the trade-off between the income and the substitution effect, we link these two strands of literature by studying family income and maternal labor supply in a unified framework. The study by Bernal and Keane (2011) is related to our work. The authors study the effect of child care versus single mothers' time inputs on cognitive outcomes for children aged 3–6. In our framework, we look also at older children and allow income to affect child investments through multiple channels: expenditures in child goods, formal child care, etc. Moreover, we do not exclusively focus on single mothers. Therefore, our study on the trade-off between monetary and time investments involves a wider population of families that better represents the population of interest to policymakers.

A second important contribution of this study derives from the analysis of the effect of family income and hours worked by the mother on a child's behavioral development. While many works exclusively focus on test scores for cognitive achievements (see Bernal and Keane, 2011; Dahl and Lochner, 2012; Del Boca et al., 2014), we extend the analysis to behavioral development.[4] Standard test scores only capture some of the multiple skills that determine individual success and well-being (Heckman and Rubinstein, 2001). Socio-emotional and behavioral skills are often more predictive of future life success than cognitive skills.[5] The analyses of cognitive and behavioral development differ substantially: while the substitution effect induced by maternal labor supply is similar for both outcomes, the income effect only appears for the analysis of cognitive development. No income effect is detected for behavioral development.

We make a third contribution by investigating the mechanism underlying the trade-off between the income and the substitution effects to draw policy suggestions from our findings. Children's poverty is a massive phenomenon worldwide with countries such as the U.S. reporting more than 21 percent of children below the federal poverty line in 2015 (National Center for Children in Poverty, 2015). Many welfare programs, such as the EITC, attempt to reduce family poverty and particularly childhood poverty by providing families with cash transfers on the condition that the recipient works. The understanding of the effects of such programs on child development is a first-order topic. Our analysis shows that in the context of programs such as the EITC, only looking at the effect of income on child development might lead to biased policy predictions. Our results on the importance of wages paid to mothers suggest that minimum wage policies might offset the substitution effect of maternal labor supply through larger income effects. Additionally, the structure of the taxation of family income potentially affects the trade-off between the income and

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

[5] For example, visit heckmanequation.org/resource/early-childhood-education-quality-and-access-pay-off/ for a discussion of the effects of the Perry Preschool Program, a high-quality U.S. preschool education program.

the substitution effects on child development. Further, policies that encourage maternal employment in low-income families should consider how to guarantee alternative sources of child care to support child outcomes.

The remainder of the paper is structured as follows. Section 2 provides a simple theoretical framework that drives the empirical analysis. Section 3 introduces the empirical model and the identification strategy. The data used for the analysis are presented in Section 4, while the results are described in Section 5. Section 6 sheds light on the mechanism underlying the main findings of the work. Section 7 concludes.

2 Reference Framework: A Model of Child Development

We introduce a theoretical framework that will guide our empirical analysis. Our framework builds on previous work of Cunha and Heckman (2007), Cunha et al. (2010), and Del Boca et al. (2014). Each agent is born with a stock of initial cognitive (θ^C) and behavioral (θ^B) skills $\theta_{\mathbf{i,0}} = \left(\theta^C_{i,0}, \theta^B_{i,0}\right)$. Let $\theta_{\mathbf{i,t}}$ indicate the vector of individual skills at each age t.[6] We define $\tau_{i,t}$ as parental time investments in the child, while $e_{i,t}$ are parental monetary investments. Each type of skill s evolves dynamically via a technology of skill formation $f^s(\cdot)$:

$$\theta^s_{i,t+1} \equiv f^s(\theta_{i,t}, e_{i,t}, \tau_{i,t}) \tag{1}$$

with $f^s(\cdot)$ strictly increasing and strictly concave in τ and e.

By assuming a standard CES technology we can write:

$$\theta^s_{i,t+1} \equiv f^s(\theta_{i,t}, e_{i,t}, \tau_{i,t}) = g^s\left(\theta_{i,t}, \left[\gamma_s(e_{i,t})^{\phi_s} + (1-\gamma_s)(\tau_{i,t})^{\phi_s}\right]^{\frac{1}{\phi_s}}\right) \tag{2}$$

[6] We define the model's periods as the individual's age t.

with $\phi_s \leq 1$ and $0 \leq \gamma_s \leq 1$. We think of the CES as an aggregator for the home investments. For each skill s, γ_s defines the relative share of expenditures (relative to time) in the combined home investment input, while ϕ_s measures the degree of complementarity between time and monetary investments.

We define the parent's utility u^P as a function of consumption c, parental leisure time ℓ, and child's skills. In this model, we include the EITC welfare benefits and its structure. The program provides a cash transfer conditional on recipients' labor supply to families with income below a certain threshold. Parents maximize their utility subject to the following budget constraint:

$$\begin{aligned} &\max_{\tau_{i,t},\ell_{i,t},e_{i,t}} u^P(c_{i,t}, \ell_{i,t}, \theta_{i,t+1}) \\ &\text{s.t. } c_{i,t} + e_{i,t} = \underbrace{\omega_{i,t} \underbrace{(1 - \ell_{i,t} - \tau_{i,t})}_{L_{i,t} \text{ (Hours Worked)}} + \widetilde{I}_{i,t}}_{= I_{i,t} \text{ (Family Income)}} + EITC_{i,t}(L_{i,t}, I_{i,t}, R^{EITC}) \end{aligned} \tag{3}$$

The budget constraint implies that the sum of consumption and monetary investments in the child must equal the sum of family income (I) and the welfare transfer (EITC). Family income is defined as the sum of earnings (ωL) and family nonlabor income ($\widetilde{I}$), while the welfare transfer in period t depends on individual labor supply, family income, and the EITC regime (R^{EITC}).

In this model, a regime expansion of EITC benefits has ambiguous effects on child development.[7] By defining a regime expansion as a change in R, it is possible to decompose the effect of the change in R on child development in two components: (i) an income effect that positively affects child development; and (ii) a negative substitution effect induced by

[7]See Figure 1 for a graphical representation of the EITC expansion in the United States in the 1987–1999 period.

less parental time invested in activities with the child.

$$\frac{\partial \theta^s_{i,t+1}}{\partial R} \equiv \underbrace{\frac{\partial f^s(\cdot)}{\partial e_{i,t}} \cdot \frac{\partial e_{i,t}}{\partial R}}_{\text{Income Effect (+)}} + \underbrace{\frac{\partial f^s(\cdot)}{\partial \tau_{i,t}} \cdot \frac{\partial \tau_{i,t}}{\partial R}}_{\text{Substitution Effect (-)}} \tag{4}$$

Equation (4) shows that the overall effect of the EITC expansion depends on: (i) inputs productivity, (ii) the elasticity of labor supply and expenditures to regime expansions, (iii) the degree of complementarity (substitutability) of monetary and time investments in the production of cognitive and behavioral skills, and (iv) the possible complementarity of home investments (money and/or time) with the current stock of skills $\theta_{i,t}$. In the following empirical analysis, we test the existence of the income and substitution effects and compare their relative magnitude in shaping child development.

3 Methodology

3.1 Empirical Model

Family environment shapes child 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 hours worked by the mother as an additional explanatory variable for child achievement. Specifically, our child outcome equation takes the following form:

$$y_{i,t} = \beta_0 + \alpha_0\, t + \alpha_1\, I_{i,t} + \alpha_2\, L_{i,t} + x_i'\, \beta_{1,t} + x_{i,t}'\, \beta_2 + \eta_i + \epsilon_{i,t}\ , \tag{5}$$

where $y_{i,t}$ represents the child's outcome in period t.[8] We focus 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 observed family i

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

fixed and time-varying characteristics. η_i reflects unobserved family specific heterogeneity that 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:

$$\Delta y_{i,t} = \alpha_0 + \alpha_1 \Delta I_{i,t} + \alpha_2 \Delta L_{i,t} + x_i' \beta_1 + \Delta x_{i,t}' \beta_2 + \Delta \epsilon_{i,t} \ , \tag{6}$$

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).[9] Equation (6) 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 development. The coefficient α_1 expresses the effect of changes in family income on changes in child development, while α_2 captures the mother's labor supply effect on changes in child development.

3.2 Instrumental Variables

The identification of Equation (6) is 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 an OLS approach. We deal with this issue by implementing an IV estimation strategy 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 (6) requires two necessary conditions for the instruments: relevance and exogeneity. Here, we describe in detail the two instrumental variables. We will discuss

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

the relevance of the instruments in Section 5.1.

3.2.1 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 in the United States. After its introduction, the EITC was progressively expanded (e.g. in 1986, 1990, 1993) to become the largest cash transfer program for low-income families with dependent children (Eissa and Liebman, 1996). In 2013, total federal EITC payments reached $63 billion given to 27 million individuals. In 2015, the program lifted about 6.5 million people out of poverty, including 3.3 million children (Center on Budget and Policy Priorities, 2016).

EITC eligibility depends on three criteria: (i) a positive earned income; (ii) on adjusted gross income and earned income below a certain year-specific threshold; and (iii) at least one qualifying child.[10] As a consequence of these criteria, the EITC primarily affects the incentive of mothers to work (Nichols and Rothstein, 2016); single mothers are the most responsive target to these incentives (Blundell et al., 2016).

The EITC income thresholds and benefits have changed over time. In Figure 1, we plot the different amounts of received transfers conditional on 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 according to a set schedule. Individual incentives and behaviors regarding labor supply may differ according to the family structure and the position (phase) on the schedule. In particular, mothers who fall into the phase-out part of the schedule may have an incentive to reduce their hours worked. However, Meyer (2002) provides evidence, at least for single mothers, that past expansions of the EITC schedules did not show this

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

type of response.

In terms of EITC federal schedule expansions over time, families with an income of around \$10,000 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 effects of the EITC on our variables of interest. EITC benefits affect family income in two ways: (i) *directly* through the tax credit transfer; and (ii) *indirectly* through labor supply responses. Consider the following after-tax total family income ($I_{i,t}$) decomposition:

$$I_{i,t} = \underbrace{w_{i,t} \cdot L_{i,t}(EITC_{i,t}) + \widetilde{I}_{i,t}}_{I_{i,t}^{pre-tax}} + EITC_{i,t}(I_{i,t}^{pre-tax}) - \tau_{i,t}(I_{i,t}^{pre-tax}) \ , \tag{7}$$

where $I_{i,t}^{pre-tax}$ represents pre-tax family income, consisting 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 $\tau_{i,t}(\cdot)$ respectively represent the EITC schedule and income tax schedule as a function of pre-tax family income.

We construct the EITC-instrument based on changes in the EITC schedules over time. These changes in the EITC schedules potentially affect both family income and maternal labor supply. To exploit only policy changes in the EITC schedules, we construct the instrumental variable as in Dahl and Lochner (2012).[11] 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.

[11] Notice that 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 and changes in marital status or household structure.

Specifically, our instrument takes the form:

$$\Delta EITC_{i,t}^{IV}\left(I_{i,t-1}^{pre-tax}\right) = EITC_{i,t}(\widehat{E}\left[I_{i,t}^{pre-tax}|I_{i,t-1}^{pre-tax}\right]) - EITC_{i,t-1}(I_{i,t-1}^{pre-tax})\ , \tag{8}$$

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 (8) are now only a function of changes in schedules.

From 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 address this concern by introducing a control function for family income ($\phi_s(I_{i,t-1}^{pre-tax})$) and augmenting our model specification as follows:

$$\Delta y_{i,t} = \alpha_0 + \alpha_1 \Delta I_{i,t} + \alpha_2 \Delta L_{i,t} + x_i' \beta_1 + \Delta x_{i,t}' \beta_2 + \phi_s(I_{i,t-1}^{pre-tax}) + \Delta\epsilon_{i,t}\ . \tag{9}$$

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:

$$E(\Delta\epsilon_{i,t}|\Delta EITC_{i,t}\left(I_{i,t-1}^{pre-tax}\right)) = 0\ , \tag{10}$$

where $\Delta\epsilon_{i,t}$ represents the error term in Equation (9). Condition (10) 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

$\phi_s(\cdot)$ about the point of predicted income for a fixed EITC schedule change:

$$\phi_s(I^{pre-tax}_{i,t-1}) \approx \phi_s\left(\widehat{E}\left[I^{pre-tax}_{i,t}|I^{pre-tax}_{i,t-1}\right]\right) + \sum_{n=1}^{k} \frac{\phi_s^{(n)}\left(\widehat{E}\left[I^{pre-tax}_{i,t}|I^{pre-tax}_{i,t-1}\right]\right)}{n!} \cdot \left(\widehat{E}\left[I^{pre-tax}_{i,t}|I^{pre-tax}_{i,t-1}\right] - I^{pre-tax}_{i,t-1}\right)^n . \tag{11}$$

The control function in Equation (11) 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 $\phi_s(I^{pre-tax}_{i,t-1}) = \widehat{E}\left[I^{pre-tax}_{i,t}|I^{pre-tax}_{i,t-1}\right]$).

3.2.2 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 maternal labor supply.

Following the approach first developed by Bartik (1991) and used in many other 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., 2017, 2018), we construct an empirical analogue of the above-mentioned thought experiment by 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 4 for more details).[12]

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

$$LabDemShocks^{IV}_{i,t} = \sum_{ind} (\ln E_{ind,-s,t} - \ln E_{ind,-s,1980}) \frac{E_{ind,se,1980}}{E_{se,1980}} \ , \tag{12}$$

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 (12) can be interpreted as the average long-term growth in employment rates by state and educational achievement.

Figure 2 graphically shows the variation of labor demand we exploit. For the sake of clarity, we report only the first year (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 college, and completed college.

Figure 2 displays changes in the employment rate over time and between different states. We first see that mothers with low and high levels of education 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. However, the employment rate for college graduates increased by 0.40 percent from 1988 to 2000. Second, we see that

[12]Moreover, we choose 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.

changes in employment rates from 1988 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 Goldsmith-Pinkham et al. (2017) show that exploiting the labor demand shocks in Equation (12) "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:

$$E(\Delta\epsilon_{i,t}|LabDemShocks^{IV}_{i,t}) = 0\ . \tag{13}$$

The condition in Equation (13) 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 (13), we introduce an augmented specification of the model in Equation (5) with state-specific trends in children's skills formation. In this way, we control for 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.[13]

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 development. However, we need the *exclusion restriction* to hold in order to interpret our IV estimates as the causal effect of family income and maternal 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 5.1 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 development through changes in the education system.

3.3 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 behavioral development. Specifically, we exploit individual scores in a combined math-reading standardized test and a standardized index for children's behavioral

[13]See Section 5.1 for the analysis.

problems.[14] 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:

$$\Delta W_{i,t} = \gamma_0 + \gamma_1 \Delta EITC_{i,t}^{IV} + \gamma_2 LabDemShocks_{i,t}^{IV} + x_i' \gamma_3 + \Delta x_{i,t}' \gamma_4 + \phi_s(I_{i,t-1}^{pre-tax}) + \Delta u_{i,t} \ , \quad (14)$$

where i represents the child and t the time period. $\Delta EITC_{i,t}^{IV}$ is the change, with respect to the previous period, in the EITC schedule experienced by child i. $LabDemShocks_{i,t}^{IV}$ stands for labor demand shocks at time t (with respect to the baseline year 1980) experienced by child 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 $X_{it} = [x_i, x_{i,t}]$ contains variables for child's gender, race, age and number of siblings. The term $\phi_s(I_{i,t-1}^{pre-tax})$ represents the third order Taylor polynomial expansion of predicted income (see Section 3.2.1). $\Delta u_{i,t}$ defines the error term (in difference).

The second stage is:

$$\Delta y_{i,t} = \alpha_0 + \alpha_1 \widehat{\Delta I_{i,t}} + \alpha_2 \widehat{\Delta L_{i,t}} + x_i' \beta_1 + \Delta x_{i,t}' \beta_2 + \phi_s(I_{i,t-1}^{pre-tax}) + \Delta \epsilon_{i,t} \ , \quad (15)$$

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.

4 Data

We use three different data sets in the baseline analysis: the National Longitudinal Study of Youth 1979 (NLSY79), the Current Population Survey (CPS), and the 1980 Census In-

[14] We introduce all details about the two outcomes of interest in Section 4.

tegrated 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, the NLSY79 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. residents 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 two years from 1986 to 2014. The sample selection rule adopted is simple: observational units include only children for whom there is information about cognitive or behavioral development. Because the children are surveyed every two years, our empirical analysis of the model in Equation (6) is based on two-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.[15] We repeat the same procedure to compute an aggregate measure of math-reading achievement as the average of the three standardized single test scores.

[15] This standardization is made on the random sample of test takers.

The second outcome of interest is the Behavior Problems Index (BPI). 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 one. We compute a comprehensive index, which is the average 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. 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 3.2.1 to compute both the after-tax family income and the federal EITC for each family and 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 noninstitutional 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

[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.

female employment rate for each cell *se* previously described in Section 3.2.2.

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 of the analysis: the sample used for the analysis of cognitive development as measured by the combined math-reading standardized test score and the one for the analysis of behavioral development as measured by the BPI. These two samples display different sample sizes as child cognitive and behavioral development are measured at different ages. Specifically, test scores cover the age range of 5–16, while the BPI covers the age range of 4–16.

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 16. 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 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.

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

5 Baseline Results

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

5.1.1 First-Stage Estimates

Table 2 displays the first-stage estimates 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. Our estimates are not threatened by weak identification of underidentification.

We start by analyzing the first stage for family income. Changes in the EITC schedule have 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 not statistically different from those estimated by Dahl and Lochner (2017) and Lundstrom (2017).

Shocks in labor demand positively affect family income. A shift in the labor demand directly affects worker compensation and family resources. 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, EITC changes induce, on average, positive shifts in the maternal labor supply. The overall positive effect is generated from several different effects such as

[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.

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. Estimates are similar for the math-reading sample (column 2) and the BPI sample (column 4). The EITC effect on labor supply is aligned with the findings in the 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.

Labor demand shocks induce changes in hours worked. 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.[19] 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 1.83 percent of her labor supply.

Our first-stage models neglect possible labor supply responses by the spouse, in the case of married couples, induced by EITC changes and shocks in labor demand. The EITC literature has found zero or very small changes for the male labor supply caused by EITC changes (Hotz and Scholz, 2003; Nichols and Rothstein, 2016). However, Equation (6) includes this endogenous responses as part of 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 a 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 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

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

that unobserved *changes* in children's skills from 1988–2000 are not correlated with the state-specific industrial compositions in the Unites States in 1980. We augment the baseline model 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 included in the baseline model. First-stage coefficients remain almost unaltered in this new setting. Even when controlling for state trends in children's skill formation, our results do not change.[21]

5.1.2 Second-Stage Estimates

Cognitive Development Table 3 reports second-stage estimates for the effect of family income and maternal hours worked on children's cognitive development as measured by the math-reading test score.[22] OLS estimates in column (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 close to 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. Measurement error is likely to affect both the measures for income and for hours worked, generating potential attenuation bias for both estimates. Moreover, income may matter more for more disadvantaged families, namely the families more affected by support programs such as the EITC. 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

[20] The state-specific trends in Equation (5) become state fixed effects in our main specification in Equation (9). 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.

marginal effects.

Instrumental variable estimates in column (2) correct 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 achieved through 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, all else being equal, leads to a 6 percent of a standard deviation decrease in math-reading test score. The effect is qualitatively comparable with previous findings in Bernal (2008) and Bernal and Keane (2011).

In the next sections, we carefully analyze the drivers of the negative effect of hours worked on 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 determines whether the income effect dominates the substitution effect of hours worked as it 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. In the IV setting in column (2), the family income effect is positive (1.3 percent of a standard deviation), although smaller than the one for cognitive development, and statistically insignificant. While changes in family income considerably affect cognitive development, behavioral development appears less sensitive (at least in the short term) to shocks in family income.

The effect of labor supply on behavioral development fairly mimics the one for cognitive development. Maternal hours worked negatively affect child behavioral development. A

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

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

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.

In column (1) of Table 5, 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] The point estimate is lower compared to the one of the baseline model (column 3). The coefficient for family income captures both the positive income effect on child development and the negative effect induced by 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 behav-

[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 deriving from sample selection criteria. 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.

ioral development, the change moves from –4 to –5.2 percent of a standard deviation. The coefficient for maternal labor supply, when analyzed in isolation, captures both the labor supply effect and the positive income effect induced by higher earnings due to increases in individual labor supply.

5.1.3 Threats to IV Estimates

We now discuss potential threats to our IV framework validity. As introduced, the existence of state-specific trends in children's skill formation would 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 unaltered 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 affect any of the results.[27]

The exclusion of variables capturing school financial and economic resources from the set of regressors might violate the exclusion restriction for the labor demand shocks instrument (see discussion in Section 3.2.2). In Table A.6, we deal with this concern by including changes over time of school finances and economic resources at the state level. This inclusion serves to test whether these excluded variables have predictive power on the outcome of interest.

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

[26] See Section 5.1.1 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's primary purpose is to make available to the public an annual state-level collection of revenues and expenditures for public education for students in prekindergarten through grade 12.

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 in revenues or expenditures over time 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. Additionally, first-stage diagnostic tests, as shown by the tests in the bottom part of the table, are unaffected in this new model specification.

Goldsmith-Pinkham et al. (2017) point out that labor demand shocks can include pre-trends that can indirectly affect the dependent variable. The existence of such pre-trends may jeopardize the validity of our identification strategy. To test for pre-trends, Goldsmith-Pinkham et al. (2017) recommend verifying 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 lagged variables, up to a maximum of six lagged years (three model periods as observations are collected every two 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 one-period lag for cognitive measures. However, when we extend the analysis to two or three periods of lagged variables, no relationship between future labor demand shocks and cognitive test scores is detected.

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

[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. Those cases represent approximately 5 percent of the entire sample.

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

5.1.4 Identifying Income and Substitution Effects with only EITC variation

In this section, we apply a new methodology developed in Agostinelli, Mogstad, and Sorrenti (in progress) that allows us to estimate our baseline model with two endogenous variables with a single instrument through the use of the income definition. The relation between family income and maternal labor supply acts as an extra source of identification, which relaxes the need for a second instrumental variable. This analysis would make easier the interpretation of results provided in the baseline analysis. In particular, by using a single instrument, we do not rely on possible different sets of compliers, and we relax the additional assumptions required for the exclusion restriction for the second instrument.

Let us consider family income as the sum of earnings, other sources of income ($\widetilde{I}_{i,t}$), and transfers from EITC program. $w_{i,t}$ represents the wage rate. We consider the same variation of EITC benefits introduced previously in the main empirical analysis. Specifically, $EITC_t(\cdot)$ is the EITC transfer function, which depends on whether the person is working or not, on pre-tax family income, as well as on the EITC regime (R^{EITC}) in period t. Then, income for family i when the child is t years old is defined as:

$$I_{i,t} = \underbrace{w_{i,t} \cdot L_{i,t}(z) + \widetilde{I}_{i,t}}_{I_{i,t}^{pre-tax}} + EITC_t(L_{i,t}\ , I_{i,t}^{pre-tax}\ , R^{EITC})\ . \tag{16}$$

In this framework, the methodology is a two-step procedure. The first step consists in the first stage of maternal hours worked with only the EITC as an instrument:

$$\Delta L_{i,t} = \gamma_0 + \gamma_1 \Delta EITC_{i,t}^{IV} + x_i' \gamma_2 + \Delta x_{i,t}' \gamma_3 + \phi_s(I_{i,t-1}^{pre-tax}) + \Delta u_{i,t}\ , \tag{17}$$

where the instrument $\Delta EITC_{i,t}^{IV}$ is the same instrument as defined in Equation (8). In the second step, we exploit the income definition and use the predicted changes in hours worked and EITC benefits to predict the changes in family income as follows:

$$\widehat{\Delta I}_{i,t}(\widehat{\Delta L_{i,t}}(\Delta EITC^{IV}_{i,t}), \Delta EITC^{IV}_{i,t}) = w_{i,t-1} \cdot \widehat{\Delta L_{i,t}}(\Delta EITC^{IV}_{i,t}) + \Delta EITC^{IV}_{i,t} \,, \qquad (18)$$

where we keep the wage rage $w_{i,t-1}$ fixed relative to the previous period to avoid exploiting changes in the compensation per hour worked.

Table 6 reports the results for the analysis with the presented methodology. The results are in line with those of the baseline analysis. First-stage estimates of maternal hours worked are similar to those in the baseline analysis with the only exception due to a small difference in sample sizes.[30] An expansion by $1,000 in the EITC schedule induces an average increase of around 145 hours worked per year by the mother. Second-stage estimates confirm the existence of a positive income effect on children's cognitive development counterbalanced by a negative and significant effect of hours worked by the mother. The income effect amounts to 2 percent of a standard deviation as a response to a $1,000 increase in family income. In terms of hours worked by the mother, an increase of 100 hours worked per year explains a decrease in the math-reading test score by 5 percent of a standard deviation. As usual, family income does not display any effect on children's behavioral outcomes, while hours worked by the mother have an effect size very similar to the one for cognitive achievements (–5 percent of a standard deviation).

5.1.5 Decomposition of the Overall Effects

We analyze here each single component of our aggregate measures for cognitive and behavioral development.[31] Such decomposition is important as it allows us to understand whether the overall effect shown in the baseline analysis is general or is driven by some specific measures for children's achievements.

[30] In the baseline analysis, only those observations with the needed information to construct both instruments are in the sample.

[31] The analysis here is based on the baseline identification strategy with two instrumental variables.

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 test scores 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 (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). 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.

5.2 Early Childhood Development

We extend the analysis to early childhood development.[32] The C-NLSY data set contains information about temperament measures collected between ages 1–7. We focus on three specific measures collected for children in this age range: compliance, insecure attachment, and sociability.[33] We express these measures in a positive scale with higher values corre-

[32]Until this point we have considered measures for cognitive performance and behavioral problems of children aged 4–16.

[33]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.

sponding 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 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.

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

6 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.

6.1 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.[34]

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.[35] For similarities with our estimating sample in the C-NLSY, we focus on households with at least one child in the same age range of the baseline analysis in the period 1985–2003.[36]

We collect 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 3 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

[34]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.

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

[36]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.

maternal hours worked (Panel A) or family income (Panel B) on each measure for time investment in child care activities.[37]

Maternal hours worked are negatively correlated with parental time investment in all five considered activities (Panel A). As an example, an increase of one hour worked per week predicts a four-minute decline per week in child care time (total child care). The result is equivalent to an average decrease in child care of approximately two hours per week if the mother starts working full time (from zero to 35 hours per week).

Panel B reports the results for family income. 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 do not deal with factors such as the quality of time parents spend with their children. Section 6.4 discusses that.

6.2 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. Given the specification in Equation (5), the causal effect of maternal hours worked on child achievement can be deconstructed in these two mechanisms as follows:

$$\frac{\partial E\left[y_{i,t}|L_{i,t}\right]}{\partial L_{i,t}} \equiv \underbrace{\alpha_1 \cdot \frac{\partial E\left[I_{i,t}|L_{i,t}\right]}{\partial L_{i,t}}}_{\text{Income Effect}} + \underbrace{\alpha_2}_{\text{Substitution Effect}} . \tag{19}$$

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

[37] 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.

(19) as:[38]

$$\frac{\partial E\left[y_{i,t}|L_{i,t}\right]}{\partial L_{i,t}} \equiv \alpha_1 \cdot \left(w_{i,t} + \frac{\partial E\left[\widetilde{I}_{i,t}|L_{i,t}\right]}{\partial L_{i,t}} \right) + \alpha_2 \ . \tag{20}$$

Equation (20) shows that 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 (20) 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 on the role played by wages.

The effect of hours worked by the mother strictly depends on labor market conditions. The recognition of sufficiently high wages potentially overcomes the substitution effect induced by decreased maternal time invested in child development: mothers 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).

In Figure 4 we exploit our baseline results for the effect of maternal hours worked on child cognitive development to graphically represent the importance of the paid wage.[39] The analysis is based on the following assumptions: (i) other sources of income do not respond to changes in maternal labor supply, and (ii) the income effect is determined only by changes in earnings. The solid line represents the overall effect of maternal labor supply (income and substitution effects) by different wage levels (x-axis). The intersection of the solid line for the effect of hours worked with the dashed horizontal line represents a zero net income-substitution effect. Such intersection highlights that up to a wage of around \$13.50 per hour, the effect induced by the extra labor income (income effect) is not enough to compensate

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

[39] 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.

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 4, we plot the wage distribution for both single and married mothers in our NLSY79 estimation sample. The biggest fractions of the wage distributions are located below the wage threshold of \$13.50 per hour.

6.3 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, other relatives, parents' friends) 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. Løken et al. (2018) show that in Norway, alternative forms of care (formal after-school care, informal care, unsupervised time at home) for children affected by a work-encouraging reform targeted at single mothers were not a perfect substitute for maternal care.

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.[40] We compare maternal educational levels by dividing the sample into two groups: mothers with at most a high school degree (*Low education*) and mothers with some college education or more (*High education*). In terms of maternal skills,

[40]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.

we separate mothers according to the median value of the AFQT test by labeling the ones with lower than median AFQT as *Low AFQT*, and those with higher than 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 years old.[41]

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.[42]

The impact of maternal hours worked is 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 close to zero. Admittedly, the group of more-educated mothers is likely to be less affected by programs such as the EITC; therefore the size of the compliers groups may differ between mothers who are less educated and those who are highly educated.[43] The analysis of maternal skills and marital status unveils similar heterogeneous patterns. Maternal hours worked do not affect child cognitive development when mothers

[41] 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.

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

[43] A similar argument applies to the case of AFQT score and marital status.

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 heterogeneous analysis for cognitive development suggests that parents from more advantaged backgrounds and with more resources, as proxied by education, skill 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 for behavioral development (Table 10, column 2). The effect of family income on child development is similar across groups. Moreover, no differential impact of maternal hours worked across subpopulations is detected either for mother's education (Panel A), mother's AFQT (Panel B), or 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 a standard deviation) of family income across different races. 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.

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.

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

Section 6.1 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.

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.[44] In 1997, the PSID complemented its main data collection with additional information on children 0–12 years old and their parents.[45] 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 nonemployed mother (LI,NE), low-income and employed mother (LI,E), high-income and

[44]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.

[45]The aim of the CDS 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.

nonemployed 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 nonemployed 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 values for the four subgroups (columns 1–4), together with the difference between employed and nonemployed mothers conditional on income group (columns 5 and 7), and its statistical significance (columns 6 and 8).[46]

Panel A of the table depicts proxies for parenting styles. Behaviors 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 monitor more when the mother is employed. For example, employed mothers report higher levels of control over the child's companions (+3 percent), activities after school (+6 percent), and homework time (+8 percent) when compared to nonemployed counterparts. Mothers with high incomes behave in the opposite way with a decrease in monitoring activities for employed mothers (–11, –13, and –10 percent, respectively).

Panel B focuses on parents' reactions to children's poor scholastic performance. A diverging pattern across income groups arises when we analyze activities such as contacting the faculty, keeping a closer eye on the child's activities, lecturing the child, encouraging the

[46]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.

child to work harder, and helping the child with schoolwork. Results in column (6) highlight that no significant change is detected for low-income mothers. These mothers do not react differently to poor scholastic performance when they are employed as opposed to when they are nonemployed. Mothers from high-income families behave differently. Employed mothers from high-income families increase contact and discussion with faculty by around 7 percent (p-val = 0.01) relative to nonemployed mothers from high-income families. 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.).[47] Four 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 Table 12 we use time diary data. School attendance is similar across income groups. Children from families with nonemployed 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 higher quality schools, etc.) this might produce a differential effect related to maternal employment. We then focus on time spent watching television.[48] In both income groups, children with employed mothers tend, or at least declare, to watch less television. This is probably due to spending less time at home. However, while

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

[48] 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.

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).[49] Similarly, maternal 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 nonemployed 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 nonemployed 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.

7 Conclusion

This paper unveils the contemporaneous effect of family income and maternal hours worked in shaping child development. We combine the analysis of cognitive and behavioral development. We exploit children's performance on standardized tests to measure cognitive development, while we use the BPI to measure behavioral development.

We find a trade-off between the income effect and the substitution effect on child development. Family income has a sizable and positive effect on cognitive development, while the income effect is statistically insignificant for 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.

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

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, and this choice likely to be affected by economic factors. We decompose the overall effect of maternal hours worked and show 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 negative effect of maternal labor supply (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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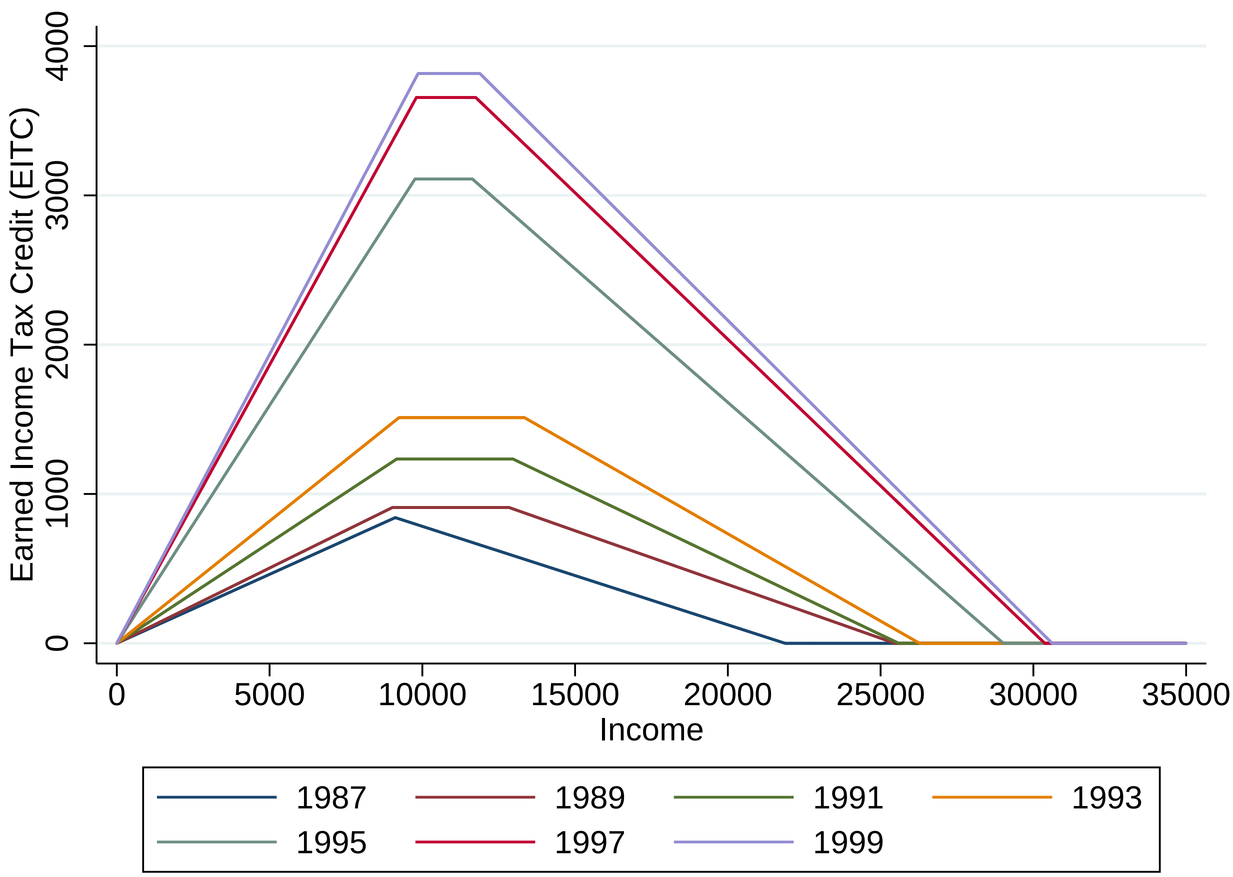
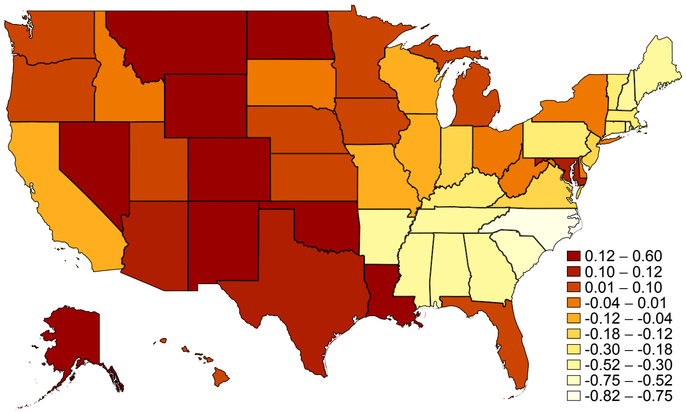
Figure 1: The EITC Expansion



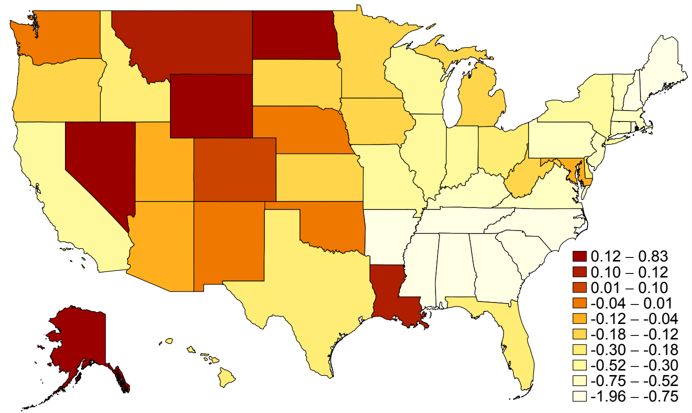
Notes: This figure shows the changes in the federal EITC schedule for families with two children. Family income is in real (2000) dollars. We calculate the EITC benefits over time using the TAXSIM program.

Figure 2: Labor Demand Shocks

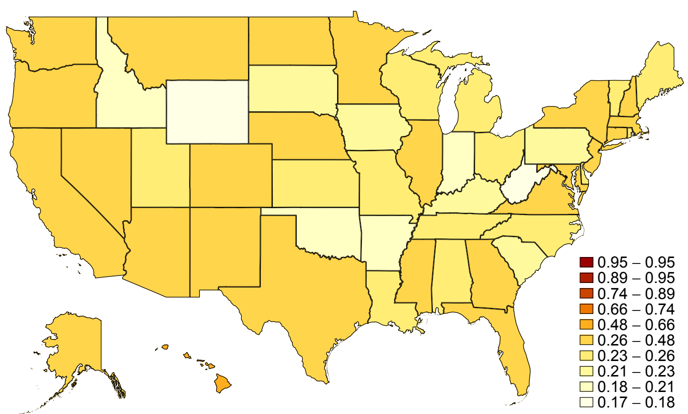
Panel A: High School Dropouts, 1988



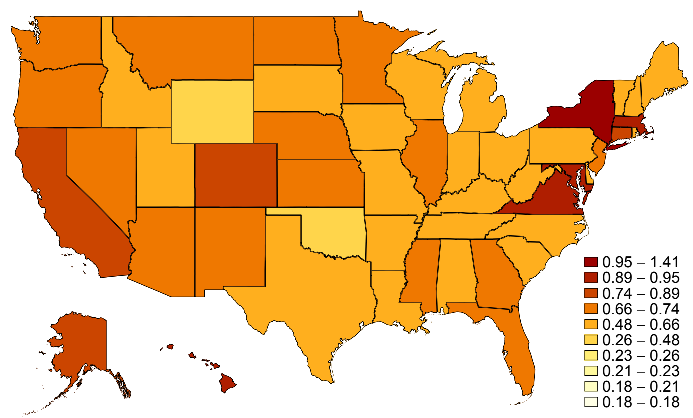
Panel B: High School Dropouts, 2000



Panel C: College Graduates, 1988

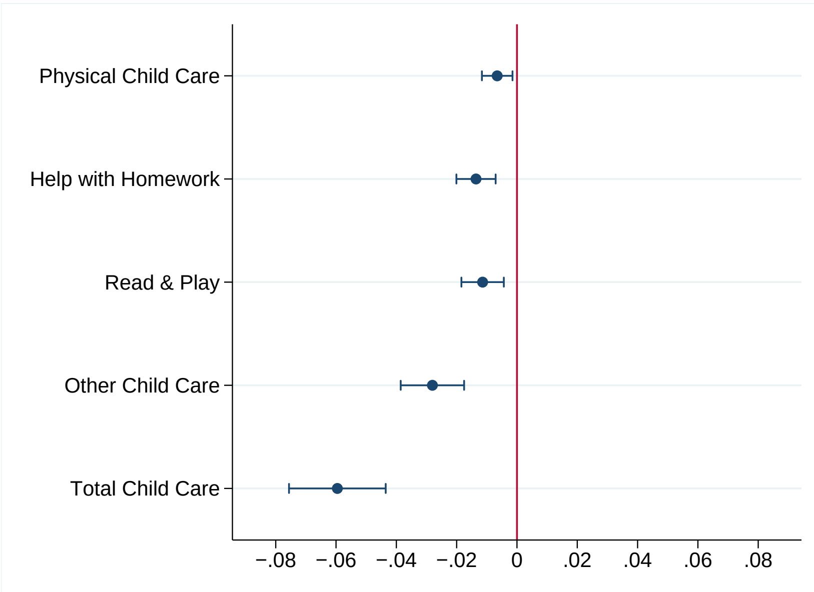


Panel D: College Graduates, 2000

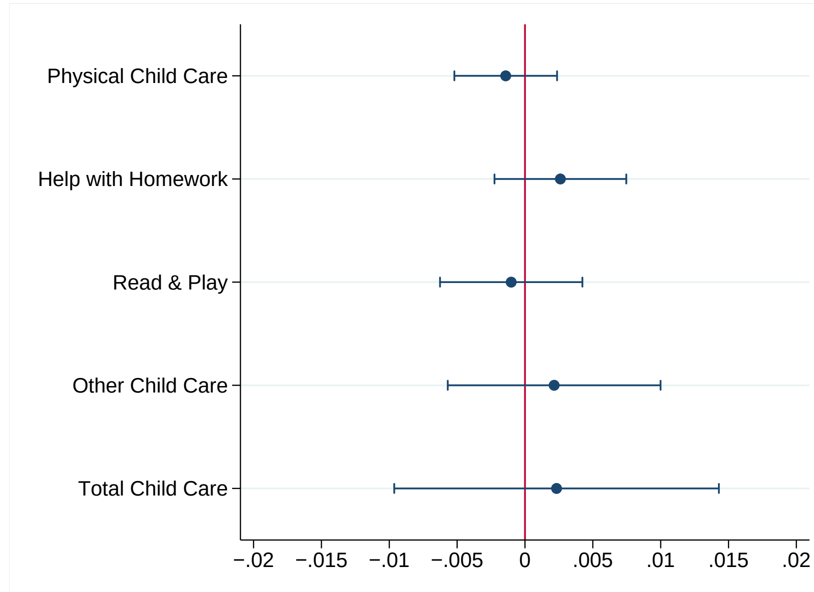


Notes: This figure shows the variation in labor demand shocks between states and over time for less-educated (school dropouts) and highly educated (college graduates) women. Panels A–B show the variation of labor demand shocks for the less-educated group. Panels C–D show the variation of labor demand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

Figure 3: 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 mother's 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 mother's 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 4: 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 mother's 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 variables: 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 worked). 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 11). 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% levels, respectively.

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

	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)
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 11). 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% levels, respectively.

Table 4: Income, Hours Worked, and Child Behavior

	Behavior Problems Index	
	OLS (1)	IV (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 11). 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% levels, respectively.

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

	Combined Math-Reading			Behavior Problems Index		
	IV (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (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 variables: 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 11). 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% levels, respectively.

Table 6: Analysis with a Single Instrumental Variable

	Combined Math-Reading (1)	BPI (2)
ΔIncome	0.020***	0.003
	(0.007)	(0.005)
ΔHours worked	-0.049***	-0.047***
	(0.016)	(0.018)
First-Stage Estimates (ΔHours worked)		
ΔEITC	1.457***	1.475***
	(0.187)	(0.182)
F-stat Excl.Instr.	60.50	65.89
Observations	12,382	13,892

Notes: This table shows the estimates for our analysis of child cognitive development (column 1) and child behavioral development (column 2) with a single instrumental variable. Dependent variables: Combined Math-Reading test score (column 1) and Behavior Problems Index (BPI) (column 2). The instrumental variable is: changes in EITC benefits (ΔEITC). 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 11). 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. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, 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 variables: 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 11). 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% levels, 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 variables: 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 11). 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% levels, 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 variables: 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 11). 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% levels, 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 variables: 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 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 11). 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% levels, 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 variables: 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 11). 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% levels, 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 for 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 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 nonemployed 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 siblings	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 variables: 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 worked). 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 11). 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% levels, 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 ($LabDemShocks$). The EITC is 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 11). 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% levels, 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 siblings	-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 11). 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% levels, respectively.

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

	Behavior Problems Index	
	OLS (1)	IV (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 siblings	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 11). 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% levels, respectively.

Table A.5: Baseline Estimates with State Trends

	Combined Math-Reading		Behavior Problems Index	
	OLS	IV	OLS	IV
	(1)	(2)	(3)	(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 in a specification with state fixed effects. Dependent variables: Combined Math-Reading test score (columns 1–2) and Behavior Problems Index (BPI) (columns 3–4). 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 state fixed effects and a third order Taylor polynomial expansion of predicted income as a control function (see Equation 11). 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% levels, 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 expenditures (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 variables: Combined Math-Reading test score (columns 1–2) and Behavior Problems Index (BPI) (columns 3–4). The two instrumental variables are: changes in EITC benefits (ΔEITC) and labor demand shocks (*LabDemShocks*). Family income, the total revenues per pupil, and the total expenditures 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. Total current expenditures per pupil is defined as the total current expenditures 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% levels, 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 (second-stage residuals). 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 variables: Combined Math-Reading test score (column 1) and Behavior Problems Index (BPI) (column 2). 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 11). 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% levels, 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 variables: Combined Math-Reading test score (columns 1–2) and Behavior Problems Index (BPI) (columns 3–4). 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 11). 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% levels, 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 variables: 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 2000 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% levels, respectively.

Appendix B: Additional Material

B.1 The Child Development Supplement

Table B.1 shows the variables construction process we use to analyze the Child Development Supplement (CDS). We focus on the first wave of the CDS (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	Show 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 for by others	Child's age when first cared for by others	0-10	Never=1
Use of rules	Family with lots of rules or not many rules	Lots, Not many	Lots=1
How often...			
Control who the child is with	Control which children your child spends 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 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 6.4. The following abbreviations are used in the table: (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.