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

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Abstract

This paper analyzes the relationship between work-promoting income transfer policies and child development. We provide new comprehensive evidence of the unintended consequences for child development of the Earned Income Tax Credit expansions during the 1990s in the United States. Our theory-driven empirical model sheds light on the trade-off between the *income* effect (economic resources) and the *substitution* effect (time and quality of the parent-child interaction) on a child's cognitive and behavioral development. This money versus time trade-off is most pronounced for disadvantaged mothers. Overall, our results call for a policy debate on how to design targeted supplements for disadvantaged families to support working mothers and their children.

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 forgone 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 from 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.

This paper provides an extensive analysis of the relationship between work-promoting income transfer policies—potentially affecting both family monetary and time resources—and child development. First, we evaluate the impact of the large expansion of the EITC during the 1990s on cognitive and behavioral development of children aged 4–16. Second, we use theory-driven exclusion restrictions to separately identify the income and substitution effects on child development, which are likely two mechanisms behind the impact on children of the EITC reforms. Finally, we provide evidence on how the EITC reforms changed parenting practices and the parent-child interaction during the period of consideration.

We develop a model of child development inspired by Caucutt et al. (2020). The technology of skill formation based on Cunha et al. (2010) allows for various degree of complementarity between time and monetary investments in child development. The impact of parental labor supply on child development can directly—through less time spent with the child—or indirectly affect the quality of the parent-child interaction.

The model conveys a clear prediction: the impact of the EITC expansion on child development is ambiguous, and it is tightly linked to the labor supply incentives for parents. A

[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 a similar program in the United Kingdom and find substantial elasticities for women's labor supply.

simulation of the 1990s EITC reform within the model suggests that the impact of the tax credit depends upon the income and the substitution effect induced by labor supply responses to the reform. On the one hand, higher disposable income, ceteris paribus, has a positive impact on child development via higher monetary investments. On the other hand, higher labor supply potentially affects the quality of the parent-child interaction, which may create unintended policy consequences for child development. Our model simulations point to the important role of wages. For high- and middle-wage parents, the income effect dominates the labor supply effect, and this in turn generates a positive effect on child development. The same reform instead leads to negative consequences for child development for children of low-wage parents due to the positive response of parental labor supply and its impact on parent-child interactions. Low wages do not allow parents to fully compensate for the diminishing time investments with substitute monetary investments. This theoretical framework sets the basis for the rest of our empirical exploration of the interactions between family choices, work-promoting policies, and child development.

Our empirical 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 the mothers of the original NLSY sample, which is a representative sample of the US youth (between 14 and 22 years old) population in 1979, and it provides longitudinal information about child development, family income, and hours worked by the mother. The sample of mothers is particularly relevant for this project, given that the major reforms of the EITC program during the 1990s were targeted primarily to mothers. 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).

We start by studying the reduced-form effects of EITC reforms on a child's development through three different empirical approaches. First, we perform an event study analysis of the largest EITC reform, which was implemented in 1993. The setup compares, pre- and post-1993, the performance of children from families who—before the 1993 reform—were either targeted by the EITC program or who were not part of the program. Second, we follow the method in Dahl and Lochner (2012) to construct a variable that captures the exogenous exposure to the policy-induced changes in EITC benefits at the family level during the 1990s. By exploiting the longitudinal dimension of the data, such variable is used in a model in first differences to identify the impact of a change in EITC benefits on the change in a child's development. Third, we exploit the policy-induced longitudinal changes in the EITC parameters, namely the changes in the maximum credit amount available given family characteristics. This alternative measure for the EITC expansion is then used again in a model in first differences to eliminate the child time-invariant unobserved heterogeneity.

Reduced-form estimates do not show any positive impact of the EITC expansion on short-term cognitive and behavioral development. Results are similar among the three empirical approaches and point to a different effect of the EITC expansion on cognitive versus behavioral development. On the one hand, the EITC effect is negative for both dimensions of a child's development. On the other hand, the effect is larger (more negative) for behavioral development. To quantify effect sizes, our preferred empirical model suggests that a $1,000 increase in EITC benefits causes a reduction by about 3 percent of a standard deviation in the cognitive score and by 5 percent of a standard deviation in behavioral development.

We rationalize our reduced-form results with respect to the existing literature by comparing our analysis with the one in Dahl and Lochner (2012), which studies the effect of family income, instrumented with the EITC expansion, on a child's cognitive development. Their study reveals positive reduced-form effects of the EITC expansion on child development. This result is, at first sight, in contrast with our reduced-form results. First, we show the importance of the different weighting schemes used in the two different empirical analyses. Second, we show that the heterogeneity of the policy impacts due to the income and the substitution effect on child development is consistent with the contrasting conclusions about the EITC policy effect.

We empirically explore the existence of the income and the substitution effect on child development. This analysis is useful to rationalize the reduced-form evidence as well as to identify the sources of possible unintended effects of the policy. First, we provide preliminary evidence of the trade-off between the income and the substitution effect by showing that families who were exposed to the EITC program before the 1993 reform experienced, post-1993, a sizable boost in both income and maternal hours worked.

To directly link the income and the substitution effect with a child's development, we perform an instrumental variable (IV) analysis. The IV strategy exploits two instrumental variables to correct for the endogeneity of family income and maternal labor supply. The first instrument is based on the constructed variable for exogenous policy-induced changes in EITC benefits. This variation captures exogenous changes in family monetary resources as well as changes in the work incentives for mothers. The second instrument we use is a measure of the local demand shocks for female labor. The local demand for labor can affect earnings and labor supply via local equilibrium effects on prices (wages).

The IV analysis confirms the existence of the trade-off between the income and the substitution effect on child development. The analysis of cognitive development shows that an additional $1,000 in family income improves cognitive development by about 4 percent of a standard deviation. The income effect 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 about 5 percent of a standard deviation. Finally, we find no evidence of a positive income effect on behavioral development, while the effect of maternal labor supply resembles the one for cognitive development. These findings suggest that money and time appear to be unequally important in the multidimensional (cognitive versus behavioral development) process of a child's development.

We take a first step to further study the nature of the money versus time trade-off by analyzing the heterogeneity of such trade-off in the population. We find that the income effect is homogeneous among cognitive and behavioral development. The same does not hold true for maternal labor supply. For cognitive development, the negative labor supply effect is more pronounced for families who are most disadvantaged, for example, single mothers, who we hypothesize have difficulty finding high-quality alternative inputs.[2] The labor supply effect is substantially homogeneous for the case of behavioral development, which is consistent with the hypothesis that parental investments in noncognitive skills are less substitutable; this lower degree of substitutability is unrelated to the socioeconomic status of the family.

In the last part of the paper, we provide suggestive evidence of the mechanisms behind the money versus time trade-off by analyzing changes in the *quantity* and *quality* of parental practices and the parent-child interaction in response to the EITC expansion. We measure our outcomes of interest via the multiple measures of the Home Observation Measurement of the Environment (HOME) section of the NLSY data. The goal of this analysis is to provide insights on the policy debate about how to contemporaneously foster maternal employment and child development. Overall, the EITC expansion does not induce parents to compensate with extra parental investments (cognitive stimulation) for the increase in hours worked and the likely reduction in the total time spent with children. Moreover, we find some evidence that the EITC expansion has negative impacts on the qualitative aspect of the parent-child interaction, with the largest reduction for both emotional support and parental involvement

[2] Bernal and Keane (2011) show that 75 percent of single mothers in the United States use informal care and that this source of care might have adverse effects on child test scores. Berlinski et al. (2020) show that high-quality childcare is essential as a supplemental input to avoid unintended consequences on children of the large increase of female labor supply over time. However, childcare might be a suboptimal solution. Baker et al. (2008) show that an expansion of childcare in Quebec increased maternal labor supply and shaped negative effects on children's aggression and social skills through, for example, the deterioration of parenting styles and lower quality parental relationships.

in children's education observed for the youngest children in our sample. These results are aligned with Kalil et al. (2022) that show that the US welfare reform in the 1990s led to no change in resources devoted by mothers to cognitively stimulate their children. On the other hand, the reform induced a decrease in the provision of emotional support, with stronger effect for mothers with lower levels of human capital.

Relationship to Literature. This article makes several contributions to the literature on child development and social policies. First, we highlight the policy-relevant relationship between policies aimed at supporting disadvantaged families via labor supply incentives and child development. In this context, policies like the EITC can generate unintended consequences for children if the program is not paired with complementary support for child development (e.g., high-quality alternatives to parental inputs).

Second, 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. Among others, studies such as Duncan et al. (1998), Blau (1999), Løken et al. (2012) and Dahl and Lochner (2012) have found evidence of the positive income effect on child achievements. 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 Rodrigues, 2009; Bernal and Keane, 2011; Carneiro et al., 2015; Del Bono et al., 2016; Løken et al., 2018; Caetano et al., 2021). There are two studies in the current literature that are most related to our work. Bernal and Keane (2011) study the effect of childcare and income on cognitive outcomes for children aged 3–6 in single-mother families. The authors find that the US welfare reforms after 1993 had negative effects on child cognitive development, with the effect occurring through childcare use. Dahl and Lochner (2012) take advantage of the quasi-experimental variation in the EITC during the 1990s to analyze the causal effect of family income on a child's cognitive achievement. In our framework, we study multi-dimensional skill development where both income and hours worked are endogenously determined inputs in the production of a child's skills. We reconcile our results on the unintended consequence of the EITC relative to the previous literature by showing how the heterogeneous labor supply responses of mothers to the EITC reforms—due to heterogeneity in the income and substitution effects of labor supply—convert into different average ex-post evaluation of the policy depending on the sample analyzed and the type of empirical setting used. Empirically, we consider various research designs to evaluate the impact of the expansion of work incentives (EITC), and we connect our results to the theory-driven predictions of the income and the substitution effect on child development. Our substitution effect can be determined by several factors, including the change in the quantity and quality of the parent-child interaction. We test these different channels in the final part of the paper.[3]

Third, while many works exclusively focus on cognitive achievements (see Bernal and Keane, 2011; Dahl and Lochner, 2012; Del Boca et al., 2014), we extend the analysis to behavioral development to proxy a set of underinvestigated soft skills with large predictive power for future life outcomes (Heckman and Rubinstein, 2001). The difference in results when looking at different sets of skills highlights the importance of this choice.[4]

The remainder of the paper is structured as follows. Section 2 describes the institutional setting and the EITC program. Section 3 provides a theoretical framework that drives the empirical analysis. Section 4 introduces the data. Reduced-form results are discussed in Section 5, and Section 6 investigates the income versus the substitution effect on child development. Section 7 sheds lights on the mechanism underlying the labor supply effect on child development. Section 8 concludes.

2 The Earned Income Tax Credit (EITC)

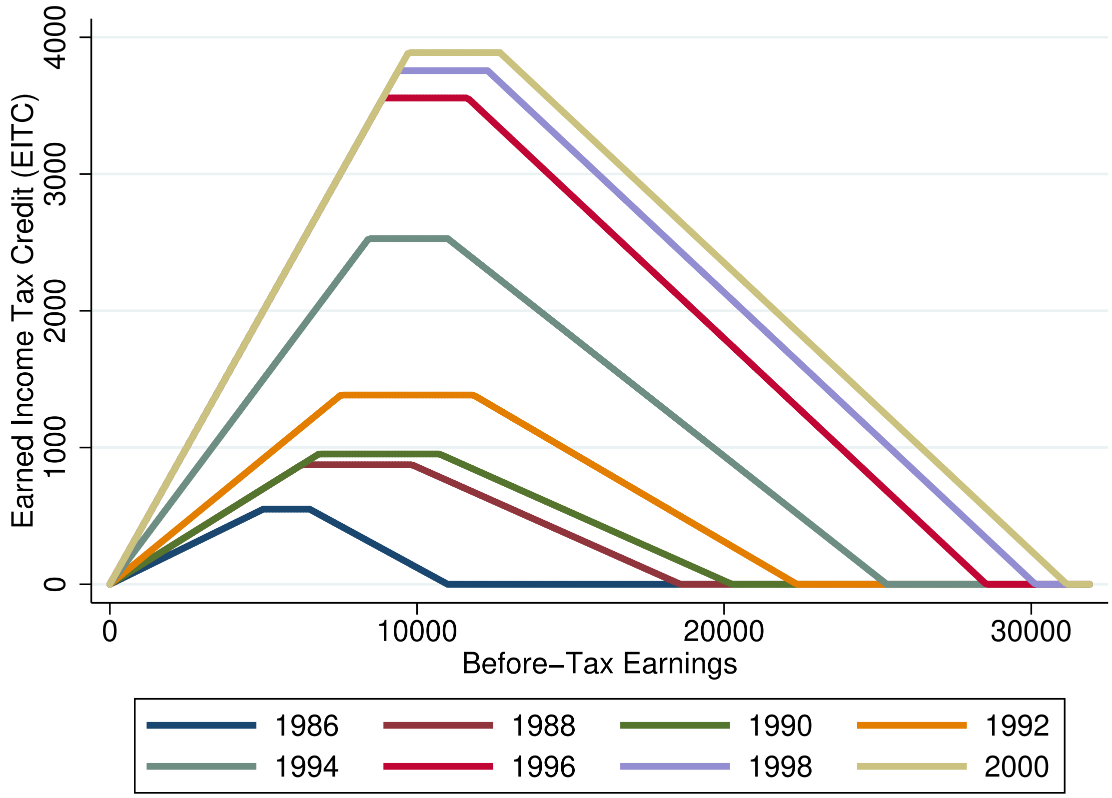
This paper focuses on the effect of work-promoting income transfer policies on child development. To do so, we study the effect of EITC and its expansion over time in the United States. Many excellent studies summarize the history of the EITC: see among others, Liebman (1998), Moffitt (2003), and Hotz and Scholz (2003). For this reason, we provide here only a brief description of the program, of its expansion, and of the program rules useful for the understanding of the theoretical and empirical analyses below.

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. Over the years, the EITC was progressively expanded. The largest expansion, in 1993, made the EITC the largest cash transfer program for low-income families with dependent children in the United States (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

[3] Fan et al. (2015) study the connection between maternal employment for married women and the educational gender gap in the subsequent generations.

[4] Our findings also provide insights on the identification and estimation of the technology of skill formation (Cunha and Heckman, 2007; Todd and Wolpin, 2007; Cunha et al., 2010; Agostinelli and Wiswall, 2016, 2020).

Figure 1: The EITC Expansion



This figure shows the changes in the federal EITC schedule for families with two children. Both before-tax earnings and EITC benefits are in (nominal) dollars. We calculate the EITC benefits over time using the TAXSIM program.

Budget and Policy Priorities, 2016).

EITC eligibility depends on three criteria: (i) a positive earned income; (ii) adjusted gross income and earned income below a certain year-specific threshold; and (iii) having at least one qualifying child.[5] As a consequence of these criteria, the EITC primarily affects the incentive of mothers to work (Nichols and Rothstein, 2016) and single mothers have been found to be 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 labor income, keeping all the family characteristics—for example, 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 the three specific phases that characterize the program. In the phase-in, the credit is a

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

pure wage subsidy. This is followed by a flat phase, after which the credit starts to gradually phase out according to a set income schedule.

In terms of EITC federal schedule expansion over time, families with an income of around \$10,000 received a transfer of around \$1,000 in 1988 or 1990. The same families received an amount that was four times higher (around \$4,000) in 2000. Section 4 will describe how we empirically construct the variable capturing EITC expansion over time.

3 Theoretical Framework

We introduce a theoretical framework that provides guidance for our empirical analysis. Our framework builds on previous work in Cunha and Heckman (2007), Cunha et al. (2010), Del Boca et al. (2014) and Caucutt et al. (2020). In particular, we present a simplified version of the model in Caucutt et al. (2020). We consider the problem of parents who care about the household's consumption and the formation of their children's skills. Parents decide how to allocate their monetary resources and time on child development, how much to consume today, and how much to save for the future. These decisions face a budget constraint, which depends upon the current EITC policy regime in place.[6]

The evolution of children's skills is characterized by the technology of skill formation, which models how current endowments and investments map into future skills for a child. We model this technology as a Constant Elasticity of Substitution function (CES) as follows:

$$\theta_{t+1} = \left[\alpha_2 \theta_t^{\phi_2} + (1-\alpha_2) X_t^{\phi_2}\right]^{\frac{1}{\phi_2}} \quad , \tag{1}$$

where θ_t and θ_{t+1} represent the current and future stock of a child's skills, respectively. X_t represents the home composite investment, which aggregates both time and monetary resources according to the following CES aggregator:

$$X_t = \left[\alpha_1 (\tau - L_t)^{\phi_1} + (1-\alpha_1) g_t^{\phi_1}\right]^{\frac{1}{\phi_1}} \quad , \tag{2}$$

where τ is the total endowment of time, and L_t defines the hours worked by the parent. $(\tau - L_t)$ represents the time parents do not work, and it aims to capture both active and

[6] In this example, we abstract from the evolution of other tax and transfer programs. For an analysis of the effects on labor supply of the interaction between the EITC and other tax and transfer programs, see Agostinelli et al. (2020).

passive parental time investments (Del Boca et al., 2014) as well as the potential impact of hours worked on the quality of the parent-child interaction. For a discussion of the importance of the parent-child interaction see Heckman and Zhou (2021) and Zhou et al. (2021). The monetary investments on a child, such as childcare and after-school care, are defined by g_t.

The budget constraint that families face is based on the total disposable income in a given period:

$$c_t + A_{t+1} + p_g \cdot g_t = w \cdot L_t + \xi_{EITC}(w \cdot L_t) + A_t \cdot (1+r) + \widetilde{I} \ , \tag{3}$$

where earnings $(w \cdot L_t)$, EITC benefits as a function of earnings according to the EITC polity regime $\xi_{EITC}(\cdot)$, income from assets $A_t \cdot (1+r)$, and other sources of nonlabor income $(\widetilde{I}_t)$ are split between today's consumption (c_t), expenditure on monetary investments for a child $(p_g \cdot g_t)$, and the next-period asset level (A_{t+1}). We define π to represent the vector of prices and exogenous income sources: $\pi = \left[p_g, w, r, \widetilde{I}\right]$. The recursive representation of the finite-horizon (T) dynamic problem for each period t can be expressed as follows:

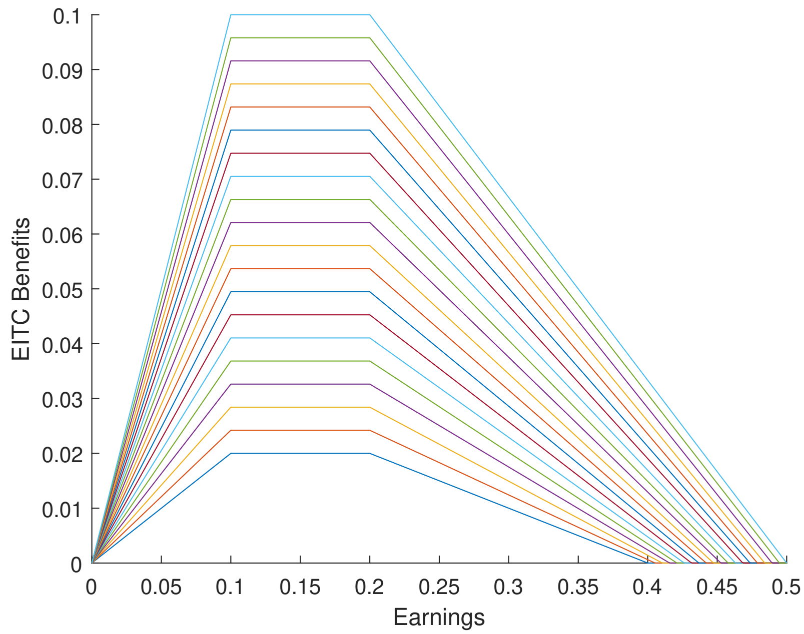
$$V_t(\theta_t, A_t; \pi, \xi_{EITC}) = \max_{c_t \geq 0, A_{t+1} \geq 0, L_t \in [0,\tau], g_t \geq 0} \gamma \cdot u(c_t) + (1-\gamma) \cdot v(\theta_t) + \beta \cdot V_{t+1}(\theta_{t+1}, A_{t+1}; \pi, \xi_{EITC}) \ , \tag{4}$$

subject to the budget constrain in (3).[7] $u(\cdot)$ and $v(\cdot)$ represent the utility functions over consumption and a child's skills, while the EITC policy regime $\xi_{EITC}(\cdot)$ defines the benefits obtained by the family, given their endogenous level of earnings.

The problem in (4) helps us highlight the key trade-off parents face when a reform changes the EITC regime. Consider a reform that expands EITC benefits for all levels of earnings E: $\xi'_{EITC}(E) \geq \xi_{EITC}(E) \ \forall E$, and $\xi'_{EITC}(E) > \xi_{EITC}(E)$ for some E. Even if the benefits are expanded for any given level of earnings, the counterfactual impact for child development is ambiguous: $\theta_{t+1}(\xi'_{EITC}(\cdot)) - \theta_{t+1}(\xi_{EITC}(\cdot)) \lesseqqgtr 0$. The ex-ante ambiguity of the impact of EITC reform depends mostly on two key mechanisms in the model: (i) the EITC-induced income and substitution effects on labor supply, and (ii) the degree of substitutability in skill production between time and goods. For instance, in the scenario in which labor supply is inelastic with respect to the incentives generated by the EITC reform, higher family income does not come at the expenses of the parent-child interaction, and the reform creates positive impact on a child's development. On the other hand, if the expansion of the program increases labor supply, higher expenditure in goods to a child can only compensate for the

[7]Given this analysis focuses on the EITC and its beneficiaries, we focus on the case in which families face a credit constraint and there is no borrowing ($A_t \geq 0$, $\forall$t).

Figure 2: Simulated EITC Expansion in the Model



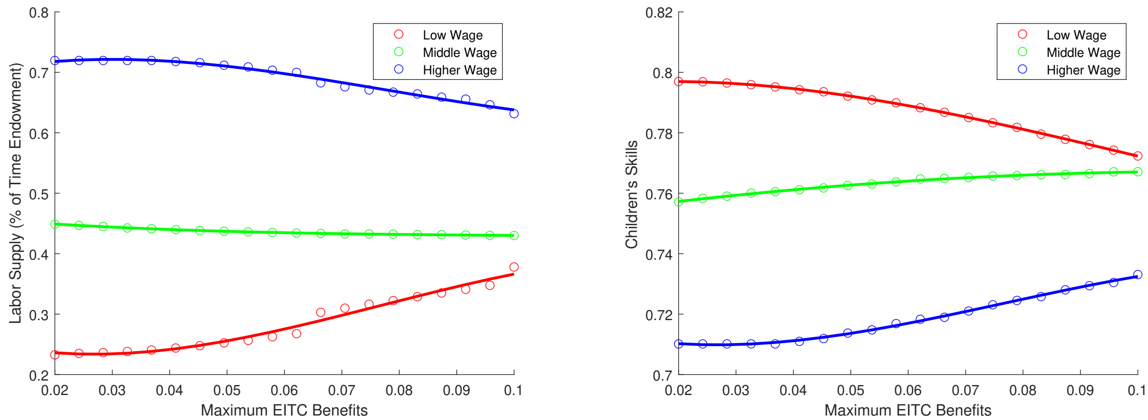
This figure shows the expansions of the EITC benefits simulated in the model. Each line represents a specific simulated EITC schedule. Earnings (x-axis) (and the associated EITC eligibility parameters) are defined as a fraction of the price numeraire. In the model, earnings are defined on a zero to one scale. EITC benefits are in the same units of earnings.

reduction in the parent-child interaction if the two inputs are highly substitutable in the production of skills.

To analyze the trade-offs in the above model, we simulate a series of reforms similar to the EITC reforms of the mid-1990s, the period of our empirical analysis. Figure 2 shows the simulated expansions of the EITC program. The features of the program and its expansion aim to reproduce the one observed in the data. In the example in Figure 2, for individuals situated on the plateau, the benefits of the program go from approximately 10-20 percent of their earnings to 50-100 percent of their earnings. Because of the nature of the program, which can be considered as a hourly wage subsidy to the workers, labor supply responds to the change in the incentives created by the tax credit expansion. On the one hand, the policy expansion can create a positive substitution effect on labor supply, especially for workers characterized by lower original wage offers. On the other hand, because the program subsidizes earnings, the same reform can create a negative income effect on labor supply for workers with relatively higher hourly wages.

For this quantitative exercise, we set log preferences over consumption (c_t) and a child's

Figure 3: Heterogeneous EITC Effects in the Model



(a) Labor Supply

(b) Children's Skills

This figure shows the endogenous realization of parental labor supply (right panel) and children's skills (left panel) as a function of the expansion of the EITC program (maximum benefits of the program, x-axis). Each dot represents the average endogenous outcome across various levels of current child's endowment and current assets (state variables θ_t, A_t) for three different levels of wage rates: low (red), middle (green), and high (blue). The three different wage levels correspond to the 20th, 50th, and 90th percentiles of wage distribution, respectively.

skills (θ_t), with a share parameter (γ) of 0.8. In the last period ($T = 3$ for this quantitative exercise), we set the continuation value to be $V_T(\theta_T) = (1-\gamma) \cdot v(\theta_T)$. As in Del Boca et al. (2014), this continuation value captures the present discounted value of the future utility derived by investing in a child. We set both the price rate for monetary investments (p_g) and the nonlabor income ($\widetilde{I}$) to one. Because we focus on values of $g_t \in [0, 1]$, this implies that families would need to spend their entire nonlabor income to purchase the maximum amount of monetary investments (e.g., childcare) for their children—although parents can still purchase a fraction of it for a fixed per-unit price. This setting is reasonable for the sample of low-income families we are analyzing. The specific parametrization of the model is: $\phi_1 = 0.5$, $\alpha_1 = 0.5$, $\phi_2 = 0$ (Cobb-Douglas), $\alpha_2 = 0.5$. This parametrization gives equal shares to time and monetary investments in the production of a child's skills, and it assumes the two inputs are relatively substitutable.

Figure 3(a) demonstrates the heterogeneity in the model of the responses to incentives for different hourly wage offers. On the x-axis, the figure shows the maximum level of the program's benefits over different simulated policy regimes, that is, the associated level of benefits at the plateau of the program schedule. On the y-axis, the figure shows the labor supply of parents as a fraction of total time endowment. The three colored lines represent the different labor supply decisions for the same family with three different wage levels: low (red), middle (green), and high (blue).[8] Keeping everything else equal—prices, today's assets, and nonlabor income—the figure shows the labor responses to an expansion of the EITC program for different wage rates. The figure confirms our previous intuition that the impact of the tax credit program on hours worked depends on both the income and the substitution effect on labor supply. For low-wage workers, the wage subsidy incentives higher labor supply, that is, the substitution effect dominates the income effect, while when we consider higher levels of wage rates, labor supply declines with an expansion of the tax credit, that is, the income effect dominates the substitution effect.

Figure 3(b) shows how the income effect and the substitution effect on the labor supply translate into child development. On the one hand, higher disposable income—ceteris paribus—can convert to higher monetary investments and subsequent higher child's skills. On the other hand, higher labor supply can impact the parent-child interaction, with possible consequences for skill development. Figure 3(b) shows that the overall impact on child development of the tax credit reform hinges on the heterogeneity in labor supply responses. For parents with high and middle wage rates, the dominant income effect on the labor supply (reduction in hours worked) induces a positive income effect on child development. The same reform instead creates unintended consequences for children of low-wage parents due to the positive response of parental labor supply and its impact on a parent-child interaction. In particular, the model suggests that the low level of wages does not allow parents to fully compensate for the lack of time investments with substitute monetary investments. In the following sections, we analyze the direct impact of the 1990s EITC reforms, and we empirically test the existence of the possible trade-off between the income and the substitution effect on child development.

4 Data and Definitions of Variables

This section describes the empirical construction of the variable capturing the EITC expansion over time. It also describes the construction of a second important variable for the empirical analysis, namely, a measure capturing exogenous local demand for (female) labor. Finally, it introduces the main data used in this study.

[8] The three different wage levels correspond to the 20th, 50th, and 90th percentiles of wage distribution, respectively.

Measuring the EITC Expansion. In our analysis, we aim to measure the longitudinal expansion of the EITC program by (i) relying on exogenous policy-induced changes in benefits each family is exposed to, and (ii) *not* relying on endogenous responses by families induced by the policy change. In other words, we construct a variable capturing the EITC expansion that exclusively relies on policy changes, as the actual change in the transfer that families receive would be 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.

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

$$\Delta EITC_{i,t} = \widehat{\xi}_{i,t} - \xi_{i,t-1} \quad , \tag{5}$$

where i indicates the child and t the period. The future EITC benefits ($\widehat{\xi}_{i,t} = EITC_{i,t}(\widehat{I}_{i,t}^{pre-tax})$) are based on the predicted family income ($\widehat{I}_{i,t}^{pre-tax}$). This way, our variable does not capture changes in the EITC benefits due to endogenous responses in the individual's labor supply and income. Predicted family income is obtained via regressing the current income on an indicator variable for positive lagged income and a fifth-order polynomial in lagged income.[9]

Measuring Local Demand for Labor. The conditions of the local economy potentially shape child development through multiple channels, for example, parental labor market conditions. We account for this by constructing a variable that works as a proxy for the performance of the local economy. As the demand for labor represents a good measure for the economic performance of a certain area, we rely on labor demand shocks as 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.

[9]Results are robust to the use of different prediction models for family income. For example, all analyses remain remarkably similar if we estimate the prediction model using only the pre-1993 data, the period before the largest expansions of the EITC program.

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., 2018a,b), we construct an empirical analog of the above-mentioned thought experiment by considering the cross-state differences in industrial composition and aggregate growth in the employment level.

Given the focus on maternal labor supply of this work, 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. We use the Current Population Survey (CPS) and the 1980 Census Integrated Public Use Microdata Series (IPUMS) to construct our measure.[10]

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

$$LabDemShocks_{i,t} = \sum_{ind} (\ln E_{ind,-s,t} - \ln E_{ind,-s,1980}) \frac{E_{ind,se,1980}}{E_{se,1980}} \quad , \tag{6}$$

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., 2020). $\frac{E_{ind,se,1980}}{E_{se,1980}}$ represents the 1980 female-employment share of industry ind for a specific education group e in state s. We consider four types of educational levels, namely high school dropout, completed high school, some college, and completed college. The variable constructed in (6) can be interpreted as the average long-term growth in employment rates by state and educational attainment.

Data. We use the National Longitudinal Study of Youth 1979 (NLSY79) for our analysis as this data set contains multiple measures for child development and family conditions.

[10]The CPS is representative of the US civilian noninstitutional population. We use an integrated version of the CPS from Integrated Public Use Microdata Series (IPUMS). The 1980 Census Integrated Public Use Microdata Series (IPUMS) allows us to construct in the most precise way employment shares in the baseline year by industry, state, and education level. 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. The following industries are considered: agriculture, mining, construction, manufacturing, transportation, wholesale trade, retail trade, finance, business service, personal service, entertainment service, professional service, and public administration.

Moreover, the information in the data is collected longitudinally. Information about children and their families is obtained by matching the information of the mothers (and the child's family) in the original NLSY79 to the additional children's survey (NLSY79-C).

As in Dahl and Lochner (2012), we restrict the analysis to the period of 1988–2000. This allows us to directly compare our findings with the previous results in the literature. Moreover, as highlighted by Dahl and Lochner (2012), this period of analysis considers the main federal EITC reforms during the 1990s, and it allows us to avoid the possibly confounding impact of the Tax Reform Act of 1986. We exclude from the analysis children whose mothers changed marital status in two consecutive periods as this might have several implications on a child's development, for example, through changes in family income due to changes in the presence of a husband in the family. Different from their work, our sample selection does not include any restriction criteria based on endogenous income levels and longitudinal changes in family income. To avoid possible concerns with predicted outliers, we trim the extreme values of the predicted exogenous trends in family income, which is a variable we construct and use as control in our main specification in Section 5.2. Finally, we use the TAXSIM program by Daniel Feenberg and the National Bureau of Economic Research to compute the after-tax family income and the federal EITC for each family and period.[11]

Given the described sample selection criteria, our observational units consist of all children for whom there is information about cognitive or behavioral development in the C-NLSY data.[12] Cognitive development is measured through achievements in math and reading activities. Specifically, we exploit the Peabody Individual Achievement Test (PIAT), which is 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). For each test, we use the raw NLSY test score data and we account for the age profile of the tests, namely, the residualized test score with respect to the child's age. We standardize each test score to obtain a measure with a mean of zero and a standard deviation of one. Finally, we compute an aggregate measure of math-reading achievement as the average of the three standardized single test scores and standardize this mean to obtain a variable with a mean of zero and a standard deviation of one.

The second outcome of interest, which captures behavioral development, is the Behavior

[11]We used TAXSIM version 32. TAXSIM allows one to calculate "federal and state income tax liabilities from survey data." See Feenberg and Coutts (1993) for further details.

[12]Siblings are part of the sample. It is important to recall that in the empirical analyses below all the inference is clustered at the family level which allows for correlation in the unobserved heterogeneity of child development between siblings.

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 (7-point scale), anxious behavior (6-point scale), headstrong behavior (6-point scale), hyperactive behavior (6-point scale), and peer conflicts behavior (4-point scale). 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. This average value is standardized to obtain a measure with a mean of zero and a standard deviation of one.

Table 1 reports the descriptive statistics for the two main samples of the analysis, namely, the sample used for the analysis of cognitive development as measured by the math-reading standardized test score and the one for the analysis of behavioral development as measured by the BPI.

Panel A of Table 1 shows that the two samples are remarkably similar; therefore, we mainly describe the one used for the analysis of cognitive development (columns 1 and 2). The average performance on the math test is about 44 (out of 84) points and the average BPI is 3.2 (out of 4.8). The average family in the sample reports a real (in year 2000 dollars) after-tax income of around $34,000, while mothers spend on average more than 1,200 hours per year working.[13] Children are assessed biennially with PIAT tests and BPI tests starting at ages 5 and 4, respectively, until they reach the age of 16.[14] Children in our estimating sample are, on average, approximately ten years old. The sample is perfectly balanced in terms of gender, while it overrepresents ethnic minorities such as Blacks (more than 30 percent) and Hispanics (21 percent). Only 9 percent of the sample consists children with no siblings; 37 percent of observations have one sibling, and 54 percent have two or more siblings. About 62 percent of observations in our sample live with married mothers, and more than 70 percent live with mothers who has, at most, a high school diploma.

Panel B of Table 1 reports information on exposure to the EITC program over years. Columns (1) to (4) focus on the sample for the analysis of cognitive development. Columns (5) to (8) focus on the sample for the analysis of behavioral development. Column (1) shows the number of children in the analysis. This number ranges between 1,318 and 2,201 children.

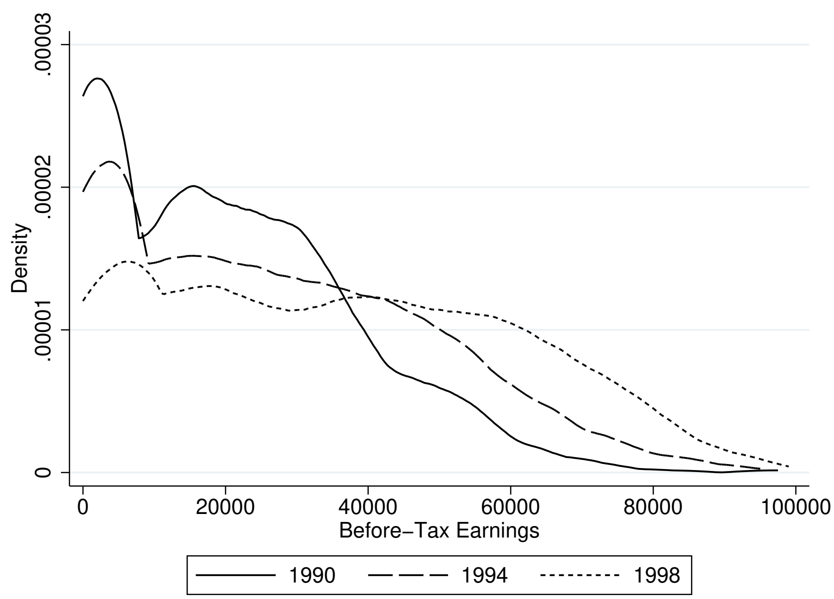
[13] All the monetary variables in the paper, unless differently specified, are in real year 2000 dollars.

[14] The fact that the collection of data on behavioral development starts one year earlier than the one for cognitive achievements is the main driver of the different sample sizes in the table.

Column (2) displays the fraction of children exposed to the EITC program; these children represent the children from mothers who are either eligible for EITC or that do not work (but are potentially affected by the EITC reform). On average, almost half of children in the sample are exposed to the EITC program. Column (3) highlights that 29 to 35 percent of children in the sample are in EITC-eligible families, namely families receiving EITC benefits. Finally, column (4) shows the increase over time of maternal yearly hours worked that move from 1,026 in 1988 to 1,477 in 2000. The analysis of the sample for behavioral development in columns (5) to (8) displays similar patterns.

Figure 4 complements Panel B of Table 1 by showing the distribution of family (nominal) before-tax earnings for a subset of years. The figure allows us to link the type of families in our sample with the EITC schedule and confirms that a sizeable proportion of sample units, specifically, about 55 percent in 1990, report family earnings below the EITC eligibility threshold, which was about $20,000 for that year (see Figure 1).

Figure 4: Earnings Distribution in the Sample



This figure shows the distribution of before-tax earnings in the sample. Before-tax earnings are in (nominal) dollars. The sample is the one used for the analysis of behavioral development.

5 The EITC Expansion and Child Development

We start the empirical analysis by studying the reduced-form effect of the expansion of the EITC program on a child's development. We perform several analyses. First, in line with many EITC-related empirical works, for example, Dickert et al. (1995), we show the event study analysis of the impact of EITC reforms on child development. Second, we estimate the impact of the EITC expansion on child development by means of the constructed variable for longitudinal changes in policy-induced EITC benefits (see Section 4). Finally, we replicate the analysis by measuring the EITC expansion with longitudinal between-states changes in the maximum amount of available benefits.

5.1 The 1993 EITC Reform: Event Study Analysis

The largest expansion of the EITC program took place in 1993. This expansion is studied in several papers such as Dickert et al. (1995), Hoynes and Patel (2018), and Kleven (2020) through difference-in-differences (DiD) or event study empirical strategies. We replicate this design in our framework. We analyze the impact of the 1993 EITC reform on both cognitive and behavioral development of children in an event study design. Because Agostinelli et al. (2020) have shown that the DiD or event study results should be taken with caution when used to causally evaluate welfare reforms, we interpret it as first suggestive evidence of the EITC's impact on children. Our event study analysis takes the following form:

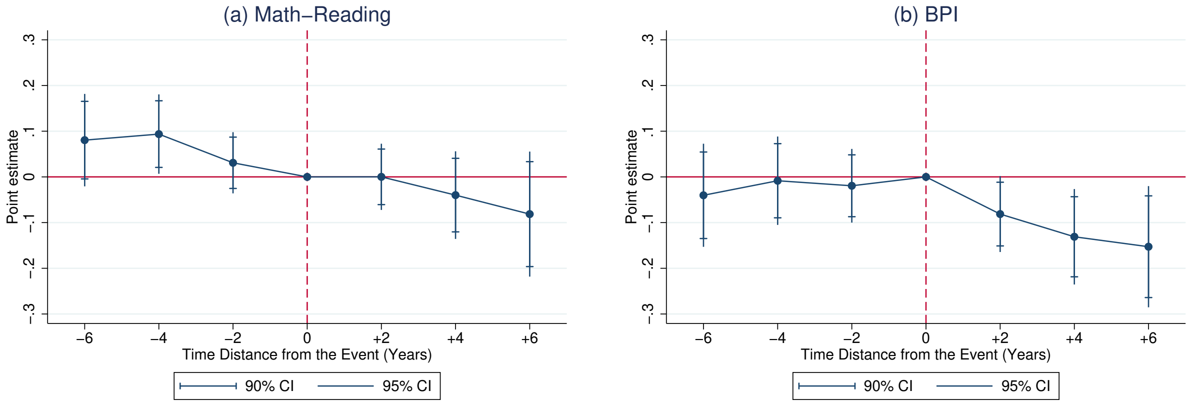
$$y_{i,t} = \beta_0 + \sum_k \beta_{1,k} Time_{k=t} \; + \beta_2 Treat_i \; + \sum_k \gamma_k (Time_{k=t} \times Treat_i) \; + X'_{i,t}\delta + \epsilon_{i,t} \quad , \qquad (7)$$

where $y_{i,t}$ represents child i's development (math-reading test score or BPI) in period t.[15] The variable $Time_{k=t}$ is an indicator that takes the value of one if the current period t is k periods away from the policy reform. The variable $Treat_i$ indicates whether the child i belongs to a family likely targeted by the EITC. Targeted families are those families that received EITC benefits at least once pre-1993 or those with members that never worked before the reform.[16] Therefore, $Treat$ separates the sample in two groups: a treatment group of families likely exposed to the EITC reform and a control group likely unexposed to the EITC reform. $X_{i,t}$ contains variables for a child's gender, age, and race, and for the number of children in the household. All these variables are also interacted with the treatment indicator to allow for

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

[16] We use TAXSIM version 32 to compute the EITC benefits received by each family in the pre-1993 period.

Figure 5: The 1993 EITC Reform and Child Development



This figure shows the evolution over time of the effect of exposure to the EITC program on child development. Dependent variables: change in Math-Reading test score (left panel), change in the Behavior Problems Index (right panel). The y-axis shows the point estimates (percent of a standard deviation) for the interaction of the indicator variable for the treatment group with indicator variables for each year. The treatment group is defined as the group of families that received EITC benefits at least once pre-1993 or those with members that never worked before the reform. The x-axis reports the time distance (in years) from the 1993 EITC reform (Time = 0). The red, vertical, dashed line visually separates the pre-reform and the post-reform periods. The model includes control variables for a child's gender, age, and race, and the number of children in the household. Each control variable is also interacted with the indicator variable for the treatment group. See text for further details. The figure reports 90 percent and 95 percent confidence intervals based on standard errors clustered at the family level.

differential trends between the treatment and the control group. We are interested in the estimates of the set of parameters γ, which capture the differential policy reform effect for the treatment group compared to the control group.

Figures 5(a) and 5(b) show the effect of the 1993 EITC reform on child cognitive and behavioral development, respectively. The x-axis reports the time difference in years from the 1993 EITC reform. The y-axis reports the point estimate, in percent of a standard deviation, for the effect of the reform on the treatment group compared to the control group. All models are estimated by clustering standard errors at the family level to allow for serial correlation of the error term over time and between siblings.

Figure 5(a) suggests that there is no positive effect of the 1993 EITC reform on a child's cognitive development. The existence of possible pre-trends implies some caution in the interpretation of the results; however, the evidence in the figure allows us to safely conclude that the reform did not positively impact a child's performance in math-reading. Indeed, in the post-reform period, the treatment and the control groups perform similarly on the math-reading standardized test.[17] If anything, four years after the reform, the treatment group seems to underperform with respect to the untreated control group. However, the point estimate is statistically nonsignificant. Two years later, the effect becomes larger, although it remains statistically nonsignificant.

Figure 5(b) depicts a different picture for the effect of the EITC expansion on behavioral development. The treatment and the control groups appear on parallel trends in the pre-reform period. After the reform, the treatment group performs worse than the control group. Two years after the reform, treated children perform, on average, about 10 percent of a standard deviation lower than the control group. The effect is statistically significant and persists two and four years later, namely four and six years after the reform.

5.2 EITC Family-Level Exogenous Policy Changes

We move beyond the event study setup—whose limits are highlighted in Agostinelli et al. (2020)—by studying the effect of multiple EITC expansions over time on child development by means of the variable for family-level exogenous policy changes. We are interested in the reduced-form effect of the EITC on a child's outcome:

$$y_{i,t} = \beta_0^{RF} + \alpha_0^{RF}\, t + \alpha_1^{RF}\, EITC_{i,t} + x_i'\, \beta_{1,t}^{RF} + x_{i,t}'\, \beta_2^{RF} + \eta_i + \epsilon_{i,t}\ , \tag{8}$$

where $y_{i,t}$ represents child i's development in period t. $EITC_{i,t}$ is the EITC transfer to child i's family. x_i and $x_{i,t}$ represent observed child fixed and time-varying characteristics as well as other contextual factors (e.g., labor market conditions) with the potential to affect a child's development. η_i reflects unobserved child- or family-specific heterogeneity that can capture any permanent unobserved family factor or child unobserved ability. The model also includes an age-trend effect in children's outcomes (α_0^{RF}). Finally, $\epsilon_{i,t}$ is the additional time-varying unobserved heterogeneity in the child's outcome, which may include unobserved child developmental shocks.

[17] We believe that possible pre-reform trends are not a concern in our framework for two reasons. First, a joint significance test of equality to zero for all the pre-event coefficients is not rejected (p-value $= 0.19$). Second, the event study analysis is based on up to six-year lag comparisons. However, our model's specification minimizes the possible concerns about long-term pre-trends in the population by comparing individuals in the population based on longitudinal variation in a narrower time span (two years). This represents one of the reasons underlying the choice of empirical models in first differences in the rest of the paper.

We take first differences to eliminate child (family) fixed effects:

$$\Delta y_{i,t} = \alpha_0^{RF} + \alpha_1^{RF} \Delta EITC_{i,t} + x_i' \beta_1^{RF} + \Delta x_{i,t}' \beta_2^{RF} + \Delta \epsilon_{i,t} \quad , \tag{9}$$

where $\beta_1^{RF} = \beta_{1,t}^{RF} - \beta_{1,t-1}^{RF}$, and where we assume that the effect of x_i on skill development is constant across development periods (β_1^{RF}). This allows us to control for differential growth in children's outcomes by observable characteristics (e.g., gender, age, race). We include in (9) the variable for changes in the local demand for female labor ($LabDemShocks_{i,t}$) to take into account the direct effect on child development of changes in the local economic conditions faced by mothers in the sample.

The policy-induced longitudinal changes in the individual's EITC benefits is constructed as in (5). The coefficient α_1^{RF} expresses the effect of exogenous policy changes in the EITC program on changes in child development over time. To take into account that the variable capturing the longitudinal EITC expansion varies not only due to the exogenous changes in the EITC schedule over time but also due to the exogenous trends in family income over the life cycle, all the analyses in the study include a set of controls for the exogenous family-specific change (trend) in the pre-tax family income. These control variables are constructed in the following way. First, we calculate the estimated exogenous trend in family income by looking at the difference between the predicted income at time t and the observed income at time $t-1$ ($\widehat{I}_{i,t}^{pre-tax} - I_{i,t-1}^{pre-tax}$). Second, we construct an indicator variable for families with positive (or negative) predicted changes in family income. Third, we interact this indicator variable for positive family income trends with the predicted change in family income and its squared terms. This set of variables aims to flexibly control for the counterfactual family income changes that would have happened in the absence of any EITC reforms.

Table 2 shows the OLS estimates of (9).[18] We focus on cognitive development as measured by the math-reading standardized test score in columns (1) and (2) and on behavioral development in columns (3) and (4). In columns (5) and (6), we combine cognitive and behavioral development by averaging each of the two standardized indexes into a combined index (development index hereafter). This development index is then standardized to have a mean of zero and a standard deviation of one. For each outcome, we estimate two different specifications. The first specification is the baseline one, and it includes control variables for a child's gender, age, and race, for the number of children in the household, and year;

[18]We compute clustered resample-based p-values via a nonparametric bootstrap algorithm as in Romano and Wolf (2016). This inference method allows us to account for the uncertainty in the predicted income used to construct the variable for policy-induced EITC changes ($\Delta EITC_{i,t}$). This inference method is used for all the specifications where we use $\Delta EITC_{i,t}$ either as a regressor or as an instrument.

it also includes the set of controls for family income trends and a variable to capture local labor demand shocks. The second specification further controls for state fixed effects to capture state trends over time. In light of the data structure, the estimated coefficients for the EITC variable should be interpreted as the effects of biennial policy-induced changes in EITC benefits on biennial changes in children's cognitive and behavioral development.[19]

The analysis of the performance in the math-reading test corroborates the event study evidence and suggests that the EITC expansion over time does not positively shape short-term child cognitive development. On the contrary, a raise in family-level EITC benefits causes a statistically significant drop in child performance. In the baseline specification in column (1), a surge in EITC benefits by $1,000 causes a 3 percent of a standard deviation reduction in the math-reading test score. The effect is similar in the specification with state fixed effects (column 2).

As in the event study setup, the EITC effect is more sizable for behavioral development. Columns (3) and (4) display that an increase of $1,000 in benefits decreases BPI by about 5 percent of a standard deviation. The effect is statistically significant and similar across specifications.

In columns (5) and (6) of Table 2 we analyze the child development index. The analysis confirms a negative effect on short-term child development implied by the EITC expansion over time. The effect amounts to about 5 percent of a standard deviation, and it is stable across specifications.

Threats to Identification. We discuss possible threats to our identification strategy by investigating the sensitivity of our baseline estimates to some changes in the estimated specifications. We focus on two possible threats: (i) endogenous eligibility to EITC benefits, and (ii) exogenous trends in child development.[20]

First, we study whether endogenous eligibility to EITC benefits potentially affects the reliability of our baseline estimates. Our constructed changes in EITC benefits depend on the

[19]The same interpretation applies to all the analyses of child development in the remainder of the paper.

[20]We also test whether the effect of EITC policy changes on the math-reading test (behavioral) score depends on a child's behavioral (math-reading) score. To do so, we augment the model in (9) with an interaction term between the variable for EITC benefits and the one-period lagged behavioral score for the analysis of math-reading. Similarly, we interact EITC benefits with the one-period lagged math-reading score for the analysis of behavioral development. The analysis reveals that in both cases the effect of EITC benefits on a child's cognitive or behavioral development does not depend on a child's previous behavioral or cognitive development, respectively. The coefficient for the interaction term is indeed remarkably small and statistically nonsignificant.

$t-1$ family income, which defines the amount of EITC benefits that each family is eligible for. However, we cannot directly control for this eligibility criteria in our regression model ($I^{pre-tax}_{i,t-1}$). In particular, suppose that earnings evolve endogenously according to the following law of motion: $I^{pre-tax}_{i,t} = \rho \cdot I^{pre-tax}_{i,t-1} + \nu_{i,t}$, where the innovation term $\nu_{i,t}$ is allowed to be correlated with the shocks in child development $\epsilon_{i,t}$. For this reason, family income is correlated with changes in the unobserved heterogeneity $\Delta\epsilon_{i,t} \equiv \epsilon_{i,t} - \epsilon_{i,t-1}$ (Equation 9), because of the simultaneous correlation between the innovation in family income and the error term ($Cov(\epsilon_{i,t-1}, \nu_{i,t-1}) \neq 0$). We follow a similar approach as in Cunha et al. (2010), where the authors exploit the limited serial correlation structure between the time-varying unobserved shocks in skill production and family income to provide exclusion restrictions (lagged family income) based on economic theory for the identification of the technology of skill formation. In our case, we control for past values of family income ($I^{pre-tax}_{i,t-q}$) as exogenous predictors for the current EITC eligibility: $Cov(\epsilon_{i,t-1}, \nu_{i,t-q})$=0 for some $q \geq 2$. In Table 3 we replicate our analysis by controlling for either the two-period (four years) lagged family income (Panel A) or the three-period (six years) lagged family income (Panel B) under different assumptions of limited serial correlation $Cov(\epsilon_{i,t-1}, \nu_{i,t-2})$=0 or $Cov(\epsilon_{i,t-1}, \nu_{i,t-3})$=0, respectively.

Table 3 reports the results for cognitive (column 1), behavioral (column 3), and the development index (column 5). As anticipated, Panel A includes two-period lagged family income, and Panel B considers the three-period lagged family income. The inclusion of lagged family income leaves all the results similar to baseline estimates. This similarity reassures that our main results do not depend upon endogenous eligibility to EITC benefits.

Second, we analyze the possible effect of exogenous trends in child development. Some of the families that are unaffected by changes in EITC benefits are families with income exceeding the EITC eligibility threshold. For this reason, a concern is that children from high-income families might experience steeper trends in math-reading test scores and behavioral measures than children from low-income families. This would generate a mechanical association between the measured changes in EITC benefits and measures for a child's development. We address this potential concern by replicating our baseline analysis on the subsample of children from families with income below \$35,000 from the previous survey wave. This income threshold (roughly) identifies the sample of families likely exposed to the EITC program and filters the possible bias induced in the whole sample by families unexposed to the EITC program due to a high level of labor income.

Table 3 shows the analysis for the restricted sample of families with one-period lagged family income below \$35,000. The analysis for cognitive development is in column (2), the analysis for behavioral development is in column (4), and the analysis of the development index is reported in column (6). In addition to the sample restriction, each specification includes as extra control variables the two-period (Panel A) or three-period (Panel B) lagged family income. Despite a natural reduction in sample size, all the results remain almost unchanged compared to the baseline analysis, therefore reassuring that exogenous trends in child development do not play an important role in shaping our baseline estimates.

Comparison with Dahl and Lochner (2012) (DL hereafter). Given the similar empirical frameworks but the discrepancies in results, we compare our reduced-form analysis to the one obtained using the framework in DL. This comparison allows to reconcile the results in this work with those in DL. Moreover, it has the potential to further motivate the analysis of the income and the substitution effect on child development as suggested by the theoretical model in Section 3.

Table 4 displays our reduced-form estimates (column 1) and the ones obtained in the DL framework (column 2).[21] The sample size is different in the two frameworks as DL exclude from the analysis families with a relatively large change in after-tax family income between two years (see footnote 12 in DL, as well as the Online Appendix for specific details). The table highlights that the estimates switch signs if our empirical model is compared to the one in DL. Indeed, the reduced-form effect induced by EITC policy changes on child math-reading test score is positive in DL, while it is negative in our framework.

To understand the determinants of the discrepancies in Table 4, we adopt the method in Løken et al. (2012) to decompose the OLS estimand in the weighted average of the underlying marginal effects and to compute the set of associated weights. This analysis allows us to: (i) highlight differences in the weighting schemes of the EITC marginal effect on children among the two studies caused by differences in the empirical framework and sample selection; and (ii) link these differences to our theory of the income versus the substitution effect on child development.

The reduced-form regression model in (9) can be generalized as:

$$\Delta y_{i,t} = \alpha_0^{RF} + \sum_{e=\underline{e}}^{\overline{e}} \alpha_{1,e}^{RF} d_{e,i,t}^{EITC} + x_i'\beta_1^{RF} + \Delta x_{i,t}'\beta_2^{RF} + \Delta\epsilon_{i,t} \quad , \tag{10}$$

where $d_{e,i,t}^{EITC} = \mathbb{1}\{\Delta EITC_{i,t} \geq e\}$ represents an indicator variable for whether family i experiences a shock in the EITC benefits at least as large as e. Following the results in

[21] In accordance to their work, DL's estimates report family-level clustered p-values.

Løken et al. (2012), we decompose the OLS estimand as a weighted average of the various marginal effects on children's outcomes:

$$\alpha_1^{RF,OLS} = \sum_{e=\underline{e}}^{\bar{e}} w_e \cdot \alpha_{1,e}^{RF} \quad , \tag{11}$$

where the weights $w_e = \frac{Cov(d_e^{EITC}, \Delta EITC_{i,t})}{Var(\Delta EITC)}$ sum to one and can be empirically computed, while $\alpha_{1,e}^{RF}$ represents the marginal effect of a one unit increase from a change in the EITC benefits from $e-1$ to e $\left(\alpha_{1,e}^{RF} = E[\Delta y_{i,t}|\Delta EITC_{i,t} = e] - E[\Delta y_{i,t}|\Delta EITC_{i,t} = e-1]\right)$.[22]

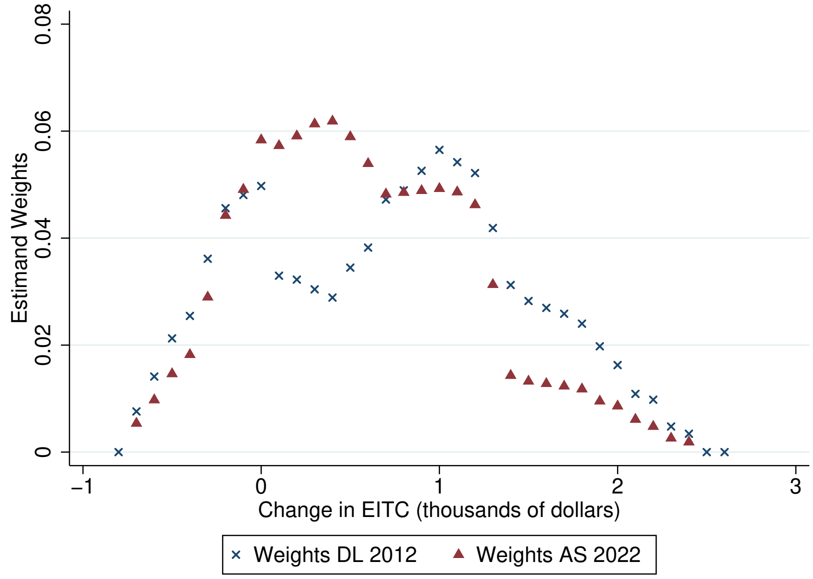
As a first step, we compute and compare the set of weights $\{w_e\}_e$ for each of the two specifications in Table 4. The comparison of the computed weights in the two frameworks provides policy-relevant insights on how the potential heterogeneous impact of the EITC reforms translates into different conclusions. . Indeed, as our theory of parental investments and child development predicts, the EITC reform can generate different incentives for the labor supply in the population (income versus substitution effects on the labor supply of mothers), and this, in turn, can translate into heterogeneous marginal effects of the EITC on children's outcomes in the population.

Figure 6 shows the set of weights given by the OLS estimand in the two empirical specifications in Table 4. The figure suggests that weights are systematically different in the two frameworks. Three different regions based on EITC policy changes are identified. In the first region, corresponding to negative changes in EITC, the OLS weights are similar across our and DL's framework and, therefore do not contribute to the different estimated effects. The second region is characterized by EITC policy changes approximately ranging between \$0 and \$1,200. In this region, the framework in DL gives much lower weights than our OLS estimand. Specifically, in some cases the weights in DL are half the weights in our analysis. Finally, in the third region, with EITC expansions exceeding \$1,200, DL gives larger weights than in our framework. The difference in weights looks sizable starting for EITC changes approximately exceeding the threshold of \$1,200.

The discrepancy in the weighting schemes motivates a detailed analysis on whether these differences in weights are associated with heterogeneous impacts of the reform in terms of labor supply and children's achievements. The focus is on those regions of the EITC benefit changes where our study and DL differ in terms of weighting schemes. Figures 7(a) and 7(b)

[22] In this case, $\Delta EITC_{i,t}$ represents the residualized variation in the change of the EITC benefits with respect to the set of controls x_i and $\Delta x_{i,t}$.

Figure 6: OLS Estimand Weights



This figure shows the set of weights given by the OLS estimand in the the framework analyzed in this study (labeled as AS 2022) versus the one in Dahl and Lochner (2012, labeled as DL 2012). Weights are computed following Løken et al. (2012). Changes in EITC benefits are defined as in Equation (5) and measured in $1,000 of year 2000 dollars. See text for further details.

show the analysis. The figures display the estimates of a nonlinear marginal effect model, where we allow the marginal effect to vary between the main EITC regions that differ in the weighting schemes among the two frameworks. The two outcomes of interest in the figure are maternal hours worked in Figure 7(a), and the math-reading test score in Figure 7(b)).

Figure 7(a) shows that changes in EITC benefits cause a sizeable labor supply response in the region where the EITC policy-induced changes in benefits range between $0 and $1,200. The estimated effect in this region suggests that a $1,000 increase in EITC benefits causes an average increase of more than 250 yearly hours worked. Again, the empirical framework in DL, compared with our regression model, underweights the contribution of these marginal effects in the aggregation process. On the contrary, DL overweighs the contribution of the marginal effects in the region of EITC, which causes smaller labor supply responses (+91 yearly hours per an extra $1,000 in EITC benefits). The difference in the weighting schemes and the evidence of heterogeneous labor supply responses are coherent with the difference between our sample and the one in DL. Indeed, DL exclude families with relatively large change in after-tax family income. This selection rule, which risks excluding from the analysis families with sizable changes in disposable income due to changes in maternal labor supply, can result in differential weighting of the estimand of the various marginal effects of the policy.[23]

Figure 7(b) displays the estimates of the same nonlinear marginal effect model directly for the math-reading test score. In line with our theory of the income and the substitution effect, the region that displays the largest labor supply responses for mothers also shows a negative marginal effect of EITC on children's outcomes. On the other hand, within the region where labor supply responses are moderate, the marginal impact of the EITC on children's learning is positive. The differential weighting schemes between our study and DL, together with the heterogeneity of the policy impacts due to the income and the substitution effect on child development, explains the contrasting conclusions regarding the policy-relevant EITC parameter in Table 4.

5.3 Expansion of the Maximum EITC Benefits

In this section, we replicate our analysis with an alternative variable for exposure to the EITC program that is measured through the longitudinal changes in the maximum federal and state EITC benefits that a family could receive, given the year, state of residence, and number of children in the household. Such measure for exposure to the EITC, independent of family income, might represent a further interesting robustness test.[24]

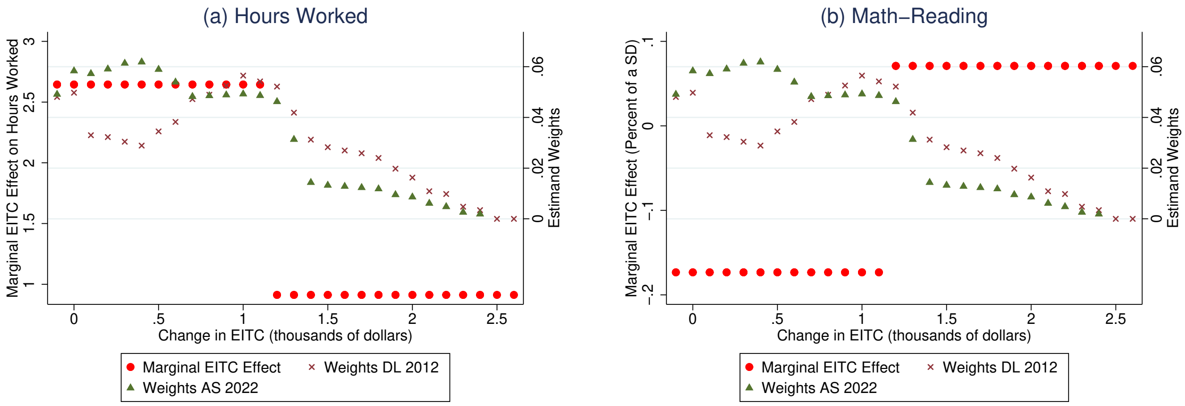
We perform this test by replicating our analysis through the use of a variable for exposure to the EITC based on the maximum level of benefits a family (couple) residing in a specific state, in a given year, and with a certain number of dependent children is exposed to. To eliminate time-invariant unobserved heterogeneity, we estimate the following regression model in first differences:

$$\Delta y_{i,t} = \alpha_0^{MAX} + \alpha_1^{MAX} \Delta MaxEITC_{s,t,k} + x_i' \beta_1^{MAX} + \Delta x_{i,t}' \beta_2^{MAX} + \Delta \epsilon_{i,t} \quad , \tag{12}$$

[23]A descriptive comparison of the sample in DL with the extra sample used in our analysis supports this intuition. On average, if we measure maternal employment status at time $t-1$, the sample in DL includes 22 percent of children with nonworking mothers, while our extra sample (excluded from DL) includes 39 percent of them (16.8*** percentage points). Because the EITC also affects the extensive margin decision, our sample of mothers is likely more exposed to large changes in hours and income induced by the reform. Similarly, the sample in DL includes 8.6 percent of children whose mother moved from nonemployment to employment between $t-1$ and t, while our extra sample includes 13.6 percent of these observations. This 5 percentage points difference, statistically significant at the 1 percent level, is sizeable and corresponds to about half of the mean value in the whole sample.

[24]A similar EITC variable has been previously used in Bastian and Michelmore (2018), who study the long-run effect of EITC exposure during childhood on education and employment outcomes.

Figure 7: Heterogeneous EITC Effects and OLS Estimand Weights



This figure shows the heterogeneous effect of the exposure to the EITC program on maternal labor supply and child development. Dependent variables: change in maternal labor supply (in hours worked per year, left panel), change in Math-Reading test score (right panel). The (left) y-axes show the point estimates for the effect of changes in EITC benefits on changes in yearly hours worked (expressed in hundreds, left panel) and test scores (expressed in percent of a standard deviation, left panel), respectively. Each panel displays the results of two separate regressions for the two EITC regions characterized by EITC changes between \$0 and \$1,200 and EITC changes exceeding \$1,200. All regressions include control variables for changes in local demand for female labor, child's gender, age, and race, the number of children in the household, year, and the set of controls for family income trends. The (right) y-axis shows the set of weights given by the OLS estimand. Weights for the AS framework refer to the model in Table 4, column (1). Weights for the DL framework refer to the model in Table 4, column (2). See the text, Table 4, and Figure 6 for further details.

where the set of control variables is the same as in (9). The variable $\Delta MaxEITC_{s,t,k}$ is the one-period (two years) change ($MaxEITC_{s,t,k} - MaxEITC_{s,t-1,k}$) in the maximum level of federal and state EITC benefits child i's family is exposed to, given state of residence s and number of dependent children k. To take into account how the EITC variable is constructed, the model is augmented with a full set of interaction terms between state (indicators) and year, the number of children (indicators) and year, and child's age (indicators) and year. The coefficient α_1^{MAX} captures the effect of a change in exposure to the EITC program measured through the longitudinal change in its maximum available benefit, on longitudinal changes in child development.

Table 5 reports the OLS estimates of (12) for cognitive (columns 1, 2, and 3) and behavioral (columns 4, 5, and 6) development, and for the development index (columns 7, 8, and 9). For each outcome, we propose a first specification estimated on the whole sample, a second specification with an extra control for four-year lagged family income, and a third specification based on the restricted sample of families with lagged (two years, namely from the previous survey wave) income below $35,000. Standard errors are clustered at the family level.[25]

Despite the use of a different measure for exposure to the EITC expansion, the analysis confirms the negative impact of the expansion on children's short-term cognitive development. The whole-sample specification suggests that an increase of $1,000 in the maximum level of EITC benefits significantly decreases the math-reading test score by 3 percent of a standard deviation. The effect does not change when lagged income is included as a control variable (column 2) and it remains negative, although it turns to being statistically nonsignificant in the restricted sample of families with income below the EITC eligibility threshold.

The expansion of the EITC program lowers children's short-term behavioral development. The analysis of BPI reveals that the EITC's effect is negative: a $1,000 increase in the maximum EITC benefits explains a 3 percent of standard deviation decrease in behavioral development. The effect is almost double in the restricted sample of families more likely to be exposed to the EITC program (column 6). The negative impact of the EITC expansion is confirmed by the analysis of the development index in columns (7) to (9).

Table A.2 reconciles this analysis with the existing literature by estimating the specification with outcome and explanatory variables as in (12) but expressed in levels.[26] The specification in levels (columns 1, 3, and 5) generates positive point estimates for the short-term effect of the EITC expansion on child development. These estimates resemble some of the estimated positive effects in the literature—see for example Bastian and Michelmore (2018). However, once we move to specifications in differences (delta) allowing for within-child estimates (columns 2, 4, and 6), the analysis depicts a different scenario with results suggesting a negative short-term impact of the EITC expansion on child development. This evidence seems to support the use of longitudinal variation in the EITC benefits, as it is robust to time-invariant unobserved heterogeneity at the family level.

Summing Up. The three different analyses reported in this section depict a coherent picture of possible unintended consequences related to the expansion over time of the EITC program. On the one hand, the estimates of the EITC effect on short-term cognitive development, although sometimes slightly imprecise, coherently point to nonpositive—and often negative—impact of the policy expansion over time. On the other hand, the effect on behavioral

[25] Table A.1 replicates the reduced-form estimates in Table 5 for a restricted sample of mothers who did not change either their state of residence or the number of children in two consecutive NLSY surveys.

[26] For example, the test (behavioral) score instead of the change in the test (behavioral) score with respect to the previous survey wave constitutes the outcome variable of the empirical model. The same definition applies to the main explanatory variable of interest, namely the maximum level of EITC benefits.

development is negative, more sizable, and always statistically significant. These results should not be interpreted as evidence of monetary family resources not having a role for child development, but instead on how labor supply incentives generated by untargeted cash transfer programs—which are alternative to programs that target disadvantaged children in terms of skill endowments—can produce potential trade-offs for child development. Our theoretical framework helps in shedding light on these trade-offs. The next section will empirically test whether the prediction of the model of the possible impact of the income and the substitution effect on child development are supported by the data.

6 The Income versus the Substitution Effect

This section investigates whether the expansion of the EITC program shaped the trade-off discussed in the theoretical framework between the income versus the substitution effect on child development. A progressively more generous program determines an income effect for families exposed to the program. Such income effect likely fosters child development. At the same time, the program structure and eligibility criteria might create work incentives for mothers. This labor supply response might affect parental time investment (quantity and quality) in child development. If this were true, the quality of alternative inputs and sources of childcare become crucial to foster child development.

We provide a dual analysis for the existence of the trade-off between the income and the substitution effect. First, we replicate the event study analysis by focusing on family income and maternal labor supply as outcomes of interest. Second, we perform an IV analysis to isolate the effect of family income and maternal labor supply on child development. The evidence obtained through this dual analysis will serve to rationalize the above-described reduced-form effects of the EITC expansion on child development.[27]

[27] See Del Boca et al. (2014), Francesconi et al. (2015) and Mullins (2016) as examples of structural models of household choices and child development that discuss the money versus time trade-off. Mullins (2016) finds that the optimal policy, accounting for children's skills, should provide higher income transfer and should minimize the labor supply incentives for disadvantaged mothers, which can in turn create unintended consequences for child development.

6.1 Event Study Evidence

We start with the event study analysis of the effect of the 1993 EITC expansion on family income and maternal labor supply. The event study specification mimics the one in Section 5.1 for child development and includes three pre- and post-reform years. The treatment group consists of those families that received EITC benefits at least once pre-1993 or those with members that never worked before the reform. With respect to the analysis of child outcomes that are measured every two years, we observe annual data for family income and maternal labor supply for the pre-1993 period.[28] We control for mother/family characteristics, namely the number of children and race. The control variables are fully interacted with the treatment variable.

Figures 8(a) and 8(b) show the analysis of family income and maternal yearly hours worked, respectively. The x-axis reports the years in which the outcome is measured. The y-axis reports the effect on family income and maternal labor supply for the treatment group compared to the control group.

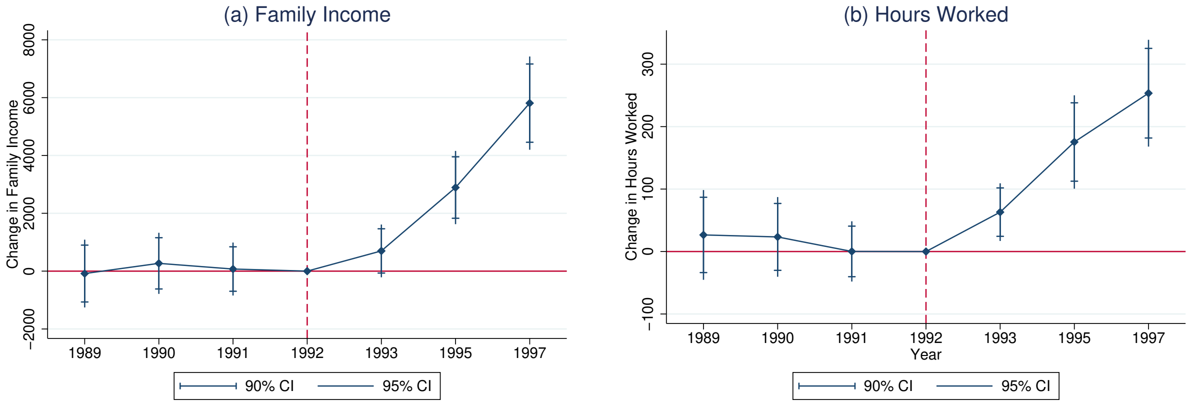
Figure 8(a) displays a sizable positive effect of the 1993 EITC expansion on family income. Pre-1993, the treatment and the control groups report identical trends in family income. Starting in 1993, the treatment effect of the reform becomes positive, statistically significant, and increasing over time. In 1993, the point estimate amounts to an extra $698 for the treatment group with respect to the control group. The effect increases to about $2,890 and $5,810 in 1995 and 1997, respectively.

The post-reform increase in family income might be driven by the increase in EITC generosity as well as by responses in maternal labor supply. Indeed, the EITC work requirements might induce mothers to work or to work more to become eligible for the EITC or to qualify for higher benefits. Figure 8(b) highlights the positive labor supply effect of the EITC expansion. Pre-reform, the treatment and control groups are on parallel trends. Right after the reform, the treatment group starts a positive trend with respect to the control group. On average, the 1993 EITC expansion increases maternal (yearly) hours worked by 63, 175, and 253 compared to the control group in 1993, 1995, and 1997, respectively.[29]

[28] Family income and labor supply information are available in the NLSY annually until the 1994 survey wave.

[29] Figure A.1 replicates the analysis of maternal hours worked by augmenting the specification with the set of controls for state welfare waivers and unemployment level (and their interaction with the treatment condition) that Kleven (2020) finds lowers the estimates of the effect of the 1993 EITC reform on single mothers' labor supply at the extensive margin. Results remain similar.

Figure 8: The 1993 EITC Reform, Family Income, and Maternal Labor Supply



This figure shows the evolution over time of the effect of exposure to the EITC program on family income and maternal labor supply. Dependent variables: change in family income (in year 2000 dollars, left panel), change in maternal labor supply (in hours worked per year, right panel). The y-axis shows the point estimates for the interaction of the indicator variable for the treatment group with indicator variables for each year. The treatment group is defined as the group of families that received EITC benefits at least once pre-1993 or those with members that never worked before the reform. The x-axis reports years. The red, vertical, dashed line visually separates the pre-reform and the post-reform periods. The model includes control variables for a child's race and the number of children in the household. Each control variable is also interacted with the indicator variable for the treatment group. See text for further details. The figure reports 90 percent and 95 percent confidence intervals based on standard errors clustered at the family level.

The event study analysis sheds light on the potential drivers of the effect of the EITC expansion on child development. The analysis highlights a potential trade-off between the income and the substitution effect. On the one hand, we observe a surge in family income with the potential to improve resources available to foster child development. On the other hand, the substitution effect induced by the increase in maternal working time might also affect a child's development, making the quality and quantity of alternative inputs crucial in the child development process. The IV analysis below will further explore this trade-off, while Section 7 will focus on changes in parental inputs induced by the EITC expansion.

6.2 IV Analysis

Empirical Model and Identification. The IV analysis aims to unveil the mechanisms behind the reduced-form results. The model in Section 3 provides useful exclusion restrictions to test the theory of the income versus the substitution effect on child development. In particular, the IV analysis allows us to isolate the single causal impact of family income and maternal hours worked on child development. The regression model takes the following form:

$$y_{i,t} = \beta_0 + \alpha_0\, t + \alpha_1\, I_{i,t} + \alpha_2\, L_{i,t} + x_i'\, \beta_{1,t} + x_{i,t}'\, \beta_2 + \eta_i + \epsilon_{i,t} \quad , \tag{13}$$

where $y_{i,t}$ represents the child's outcome (math-reading test score or BPI) in period t. $I_{i,t}$ and $L_{i,t}$ reflect the after-tax total family income and the maternal labor supply (yearly hours worked) at time t. All other variables in the equation are the same as in (8).

First differences allow us to eliminate child (family) fixed effects and to obtain our baseline IV specification:

$$\Delta y_{i,t} = \alpha_0 + \alpha_1 \Delta I_{i,t} + \alpha_2 \Delta L_{i,t} + x_i' \beta_1 + \Delta x_{i,t}' \beta_2 + \Delta \epsilon_{i,t} \quad . \tag{14}$$

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, and α_2 captures the effect of changes in yearly hours worked on changes in child development.

The identification of (14) 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 exclusion restrictions of the two variables constructed in Section 4: longitudinal exogenous changes in the EITC schedule ($\Delta EITC_{i,t}$) and longitudinal variation in local demand for female labor ($LabDemShocks_{i,t}$).

The conditional independence of the instrumental variables is sufficient to interpret as causal the reduced-form effect on child development. However, the IV framework requires the exclusion restrictions for the two instruments to hold in order to interpret our estimates as the causal effect of family income and maternal labor supply. The EITC variable is constructed to isolate exogenous changes in the policy without relying on any endogenous response at the child or family level. The exclusion restriction of local demand for female labor 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 and childcare industries. We will perform a specific test below to test the reliability of the exclusion restriction for the instrument based on local labor demand.

With these two instruments available, we estimate the following first stage for each of the endogenous variables $\Delta W \in \{\Delta I, \Delta L\}$:

$$\Delta W_{i,t} = \gamma_0 + \gamma_1 \Delta EITC_{i,t} + \gamma_2 LabDemShocks_{i,t} + x_i' \gamma_3 + \Delta x_{i,t}' \gamma_4 + \Delta u_{i,t} \quad , \tag{15}$$

with variables defined as usual. The second stage becomes:

$$\Delta y_{i,t} = \alpha_0 + \alpha_1 \widehat{\Delta I_{i,t}} + \alpha_2 \widehat{\Delta L_{i,t}} + x_i' \beta_1 + \Delta x_{i,t}' \beta_2 + \Delta \epsilon_{i,t} \quad , \tag{16}$$

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.[30]

IV Estimates. We estimate two versions of (16). The first specification, our baseline model, includes controls for a child's gender, age, and race, for the number of children in the household, year, as well as the set of controls for family income trends. The second specification further controls for state time trends by adding state fixed effects. Indeed, the possible existence of state-specific trends in children's skill formation represents a potential threat to the validity of our IV analysis. The conditional independence of the instrument based on labor demand shocks requires that unobserved *changes* in children's skills in 1988–2000 are not correlated with the state-specific industrial compositions in the Unites States in 1980.

Table 6 reports the first-stage estimates.[31] We start by analyzing the first-stage results for the baseline specification without state fixed effects. Column (1) displays the first-stage estimates for family income. The expansion of the EITC has a positive effect on family income. A \$1,000 increase in EITC benefits induces a \$1,580 increase in after-tax family income. The size of the effect of the EITC expansion is in line with expectations. Indeed, a coefficient larger than one masks the two main effects implied by the EITC expansion. First, an increase in EITC generosity translates into higher family income. Furthermore, the EITC effect on maternal labor supply, anticipated in the event study analysis, also implies additional earnings at the family level. The second instrumental variable has the expected sign: positive shocks in the local demand for female labor boost family income. An upward shift in the labor demand directly affects worker compensation and family resources. In our

[30]Given that we are not able to characterize the possible groups of "compliers" for the two instruments, we do not interpret the estimates as local average treatment effects. We interpret the IV analysis as an empirical test of the mechanisms—the income and the substitution effect on child development—underlying the reduced-form results discussed above.

[31]For the sake of brevity, we only report the first stage for the sample used for the analysis of cognitive development. The whole set of first stages is reported in Table A.3.

framework, an increase by 1 percent in the employment rate relative to 1980 predicts an increase of about $1,850 in after-tax family income.

Column (2) of Table 6 presents the first-stage estimates for maternal hours worked. In our sample, increases in EITC benefits induce, on average, positive shifts in maternal labor supply. A $1,000 increase in EITC benefits causes an average increase of about 212 yearly hours worked. The EITC effect on labor supply is aligned with the findings in the literature summarized in Nichols and Rothstein (2016).[32] Shocks in local demand for female labor induce changes in hours worked. A 1 percent surge in the employment rate relative to 1980 induces an increase of around 43 yearly hours worked by mothers. This means that, for the average mother who works 1,265 hours per year (see Table 1), a 1 percent increase in the employment rate in her local labor market causes an increase of more than 3 percent of her labor supply.

Table 6 also shows that first-stage estimates remain similar in the specification with state fixed effects. Similarity holds both for family income (column 3) and maternal labor supply (column 4). If anything, the coefficient for the EITC effect on family income tends to become slightly larger (1.87 versus 1.58) while, controlling for state fixed effects, approximately doubles the effect of labor demand shocks in both first stages.

Importantly, in addition to the evidence of strongly significant first-stage coefficients in both specifications, the bottom part of the table displays the diagnostic tests for each first stage. All the tests suggest that the instruments work particularly well in both specifications and that our estimates are not threatened by weak identification or underidentification.

Table 7 reports second-stage estimates. Columns (1) and (2) of the table report estimates for the effect of family income and maternal hours worked on children's cognitive development. In the baseline specification in column (1), family income positively affects a child's cognitive achievement. A $1,000 increase in after-tax family income, ceteris paribus, generates a 4 percent of a standard deviation increase in the math-reading test score. This result, although achieved through a different estimation framework, is aligned with Dahl and Lochner (2017).[33] Conversely, an increase in maternal hours worked induces a statistically significant negative effect on the math-reading test score. A 100-hour per year increase in maternal work, all else being equal, leads to a 5 percent of a standard deviation decrease in the score.

[32]This result also aligns with the sizable and positive EITC effect on single mothers' labor supply found in Agostinelli et al. (2020).

[33]Dahl and Lochner (2017) find that an additional $1,000 of family income causes an increase of 4.1 percent of a standard deviation in children's cognitive achievement.

Augmenting the specification with state fixed effects (column 2) leaves the results unaltered.

Columns (3) and (4) of Table 7 show the IV analysis of behavioral development as measured by the BPI score. In column (3), the income effect on child behavioral development is negligible (about 1 percent of a standard deviation) and weakly significant. In column (4), with state fixed effects, the coefficient turns to be statistically nonsignificant. 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 affects child short-term behavioral development. A 100-hour per year increase in maternal work causes a 3 percent of a standard deviation decrease in short-term behavioral development regardless of the empirical specification analyzed.

Finally, in columns (5) and (6) we analyze the development index consisting of both the cognitive and the behavioral dimensions. The analysis reveals the existence of a positive and significant income effect counterbalanced by a negative impact of maternal labor supply.

We run some robustness tests for our IV estimates. As for the reduced-form analysis, in Table 8 we test concerns of endogenous eligibility to EITC benefits and exogenous trends in child development. To this purpose, in Panel A of the table, we augment our specification with the two-period (four years) lagged family income. In Panel B, we use the three-period (six years) lagged family income. Moreover, in columns (2), (4), and (6), we further restrict the analysis to the sample of families with initial income at $(t-1)$ below \$35,000.[34] Qualitatively, all the specifications display similar results with evidence of the trade-off between the income and the substitution effect on child development. From a quantitive viewpoint, in some cases, point estimates are slightly larger than the baseline ones. However, two aspects are worth noting. First, the income effect is again always positive and larger for cognitive development than for behavioral development. The labor supply effect arises independently on the outcome variable. Second, the ratio between the income and the labor supply coefficient is similar to the one in the baseline analysis, therefore suggesting the same degree of income versus hours worked substitutability. Overall, this analysis reassures us of the stability of IV estimates to different strategies to test our concerns.[35]

[34] Section 5.2 describes the intuition underlying these tests.

[35] As a further robustness check, we analyze the effect of a family's total hours worked. Table A.4 in the Appendix shows the results when we consider total hours worked at the family level (mother and spouse) instead of maternal hours. The results are unchanged. Results are also unchanged if we replicate IV estimates after augmenting the model with variables for school financial and economic resources, that is, the change in per pupil total revenues and per pupil total current expenditures by state and over time (data source: CDD National Public Education Financial Survey). This specification allows to consider that local labor

6.3 Heterogeneity in the Trade-Off

This section replicates the baseline analysis by focusing on various subpopulations of interest. We look for evidence of heterogeneous treatment effects induced by the EITC expansion. We aim to understand whether the effect of the EITC expansion is similar for different subgroups of mothers or children. For policy-making purposes, we are particularly interested in further exploring the negative effect of EITC-induced surges in maternal hours worked on child development before we discuss parenting practices and investments in Section 7.1.

The effect of maternal labor supply might be driven by (at least) two different factors. First, increases in maternal labor supply might decrease the quantity and quality of parental time investments in child development. Second, surges in parental working time might affect the child-parent attachment as well as parental opportunities to monitor a child's development and activities. Therefore, the quality and nature of alternative inputs and forms of childcare used to replace (or complement) parental time become crucial to avoid slowing down the child development process. However, high-quality alternative inputs might be unavailable, unaffordable, or unknown to parents. Bernal and Keane (2011) show that the very prevalent sources of informal care—grandparents, siblings, other relatives, or parents' friends—have adverse effects on child development as measured through test scores. Løken et al. (2018) show that in Norway, alternative forms of care, such as, 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. Similar results, with emphasis on children's noncognitive skills, arise in Baker et al. (2008). We start with the analysis of the existence of possible heterogeneity in the treatment effect, and in Section 7.1, we home in on time investments with an emphasis on the distinction between quantity and quality time.

We investigate three different sources of heterogeneity: maternal educational level, maternal marital status, and child's age. We compare maternal educational levels by dividing the sample into mothers with at most a high school degree (*Low Education*) and mothers with some college education or more (*High Education*). We analyze marital status by comparing married mothers with unmarried mothers. Finally, we study heterogeneous effects by a child's age by dividing the sample into children younger and older than 12 years old.

demand shocks might affect employment and the allocated resources in the education industry, therefore undermining the exclusion restriction of the instrument based on local demand for female labor. For the sake of brevity, we do not report these results.

We run two different analyses. The first analysis resembles the one in Section 5.2 and focuses on the subgroups' reduced-form effect on child development of the EITC expansion over time. Table 9 shows the reduced-form estimates (by subgroups) for a specification including only the standard control variables and an additional one augmented with state fixed effects. We analyze cognitive (columns 1 to 4) and behavioral (columns 5 to 8) development. The second analysis, reported in Table 10, performs the IV estimates as in Section 6.2 to isolate the income versus the labor supply effect on child cognitive (columns 1 and 2) and behavioral (columns 3 and 4) development.[36]

We start with the reduced-form analysis of cognitive development. The analysis by maternal education highlights that the negative effect induced by the EITC expansion only arises for mothers with low education. Conversely, for highly educated mothers, the EITC expansion has no impact on cognitive development. The IV analysis displays a similar income effect by educational subgroups. However, in the specification in column (1), the labor supply effect is only significant for mothers with low education (-4 percent of a standard deviation). The specification with state fixed effects in column (2) displays similar impact by maternal education level. The analysis of marital status displays a negative reduced-form effect of the EITC expansion only for the group of unmarried mothers—see Table 9, columns (3) and (4) of the second panel. For married mothers (columns 1 and 2), the effect turns to a positive value. Unmarried mothers constitute the only group of mothers with significant negative labor supply effects in the IV analysis in Table 10 (columns 1 and 2 of the second panel). Overall, the analysis of cognitive development by mother's education and marital status seems to suggest that the negative effect of hours worked shown in the IV analysis in Section 6.2 seems to be mainly driven by the subgroup of mothers likely to experience more difficulty accessing high-quality alternative inputs. For instance, mothers with higher educational levels are likely to have easier access to better resources and higher quality alternative inputs for their children, therefore possibly mitigating the negative impact induced by their increase in individual labor supply. Similarly, results by marital status seem to suggest that married mothers might have easier access to alternative forms of formal or informal childcare, for example, partner's time, to compensate for a surge in maternal labor supply.

Younger children seem more affected by the EITC expansion. The EITC reduced-form

[36] We decompose our predicted exogenous changes in our two endogenous variables in a two-stage least squares fashion, in which we allow the second-stage coefficients for income and hours worked to vary by mother's level of education, marital status, and child's age. We implement a family-level clustered bootstrap procedure (100 repetitions) to obtain the adjusted p-values. For the sake of brevity, we do not report heterogeneous analysis for the development index. Results for this analysis display similar patterns as the ones for the other outcomes.

effect is statistically significant only for children under the age of 12. Moreover, despite a homogeneous income effect by age subgroups, Table 10 shows that the negative effect of maternal hours worked is slightly larger for younger children. The effect induced by maternal labor supply might be larger when the child is younger and needs more supervision and parental care. Heterogeneity by age in the response to the EITC expansion is further discussed in Section 7.1.

The analysis of behavioral development depicts a different picture. With the exception of age, the reduced-form estimates of the EITC expansion are negative and similar for all subgroups. By maternal education, the negative impact of EITC expansions is similar across subgroups although more statistically significant for mothers with low education. For marital status, the point estimates are larger, although slightly more imprecise, for married mothers. Finally, the EITC expansion seems more detrimental for younger children, while the effect is negative but nonsignificant for older children. The IV analysis points to the absence of the income effect on behavioral development; the negative impact of maternal labor supply is quite homogeneous across population subsamples.

The heterogeneous analysis for cognitive and behavioral development further highlights the different accumulation process for cognitive versus behavioral skills. The negative impact of maternal labor supply on short-term cognitive development appears to be mainly driven by the quality level of the alternative inputs in the child development process. For mothers from more-advantaged backgrounds and with more resources, as proxied by education and marital status, there is less evidence of a detrimental impact of maternal labor supply on short-term child cognitive development. These parents likely employ high-quality alternative inputs for the child when an increase in individual labor supply occurs.[37] Alternatively, they are able to more productively substitute the quantity of time with the quality of time devoted to their children. The same does not hold true for behavioral development. In line with the recent results by Kalil et al. (2022), we find that surges in labor supply are unlikely to be effectively compensated through alternative inputs.

[37]Our findings are consistent with Berlinski et al. (2020), who find, in a structural model framework, that access to high-quality childcare services is a key input for child development while supporting working mothers. Our results are also in line with Rodríguez (2020), who analyzes the workfare experiment “New Hope” in Milwaukee. The author finds that when the EITC expansion and work requirements are bundled with generous childcare subsidies, the reform did not generate unintended consequences.

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

This section digs into the mechanisms behind the impact of maternal hours worked on child development. This analysis is crucial to inform policymakers about the trade-off some policies might generate and on tools with the potential to contemporaneously foster maternal employment and child development. First, we analyze how parenting practices and investments respond to the expansion of the EITC program. Second, we analyze the effect on child development of local shocks on the labor market demand for female labor. This analysis unveils that maternal labor supply is not per se detrimental when it comes to children's short-term cognitive and behavioral development. Indeed, the analysis highlights that labor demand shocks—likely generated by growth in local labor market productivity—are important predictors of female labor supply and, as they likely boost the return of working, they do not negatively impact child development.[38]

7.1 Quantity and Quality Responses of Parental Investments

Did parents change their behavior and educational activities with their children in response to the EITC expansion? Did the quality of the parent-child interactions change? The answers to these questions inform our understanding of the mechanisms behind the substitution effect on child development induced by labor supply. An endogenous increase in investments (quantity) in the home environment and educational activities could offset the potential unintended consequences of the EITC expansion on child development. At the same time, a deterioration of the quality of the parent-child interactions, for a fixed quantity, could negatively affect a child's development.

We study parenting practices and quality of the parent-child interactions through the lens of cognitive support, emotional support, and involvement in a child's education. We measure cognitive support with the NLSY Cognitive Stimulation Score. The cognitive stimulation score proxies the level of cognitive stimulation in a child's home environment. The score is based on combined information as reported by the mother and the interviewer. For example, the mother reports the number of books available to the child, about parent-child reading activities, whether there is a musical instrument in the home, whether there are newspapers

[38] See for example Ngai and Petrongolo (2017) for a discussion on how structural transformation and the rise of the service industries narrowed the gender gaps in hours and wages in recent decades.

at home, etc. The interviewer reports her own impression on the overall quality of the home environment covering, among other things, aspects related to the rooms' luminosity and cleanliness. The mother's and interviewer's answers are then used to construct an overall score on a 160-point scale. Given the nature of the items, the cognitive stimulation score seems to better capture elements related to the "quantitative" aspect of the parental investment in child development.

We proxy the quality of the parent-child interaction with the NLSY Emotional Support Score. This score captures the level of emotional support each child is exposed to in the home environment. Also this score is based on combined information as reported by the mother and the interviewer. The mother reports about parental warmth (e.g., the quality of the interaction with parents, frequency of interactions with other people such as relatives and friends) or a child's involvement in home activities (e.g., making her own bed, cleaning her own room, bathing herself). The interviewer describes the mother-child interaction during the interview covering aspects related to the tone used by the mother to deal with the child or the attempt of the mother to actively involve the child in her interview. The mother's and interviewer's answers are then used to construct an overall score on a 140-point scale. The emotional support score appears to be more adept at proxying elements related to the "qualitative" aspect of the parental relationship (and investment) with the child.[39]

Finally, we measure maternal involvement in a child's education by considering the response to a child's poor scholastic performance. The NLSY data inspect several possible maternal reactions in response to hypothetical low school grades. In particular, each mother is asked to report on the seven following reactions to low grades: contact teacher or principal, lecture child, supervise child more closely, talk with child, see if child improves on own, tell child to study more, help more with schoolwork.[40] Each variable is expressed on a 5-point scale from "Very likely" (1) to "Not at all likely" (5). To simplify interpretation, we have reverted the scale so that larger values imply a more intense maternal response to low grades.

We estimate the reduced-form effect induced by exogenous EITC policy changes on changes

[39]Refer to the NLSY website for more detailed information on the home environment scales and the full list of variables used for their construction. The cognitive stimulation and emotional support subscales are validated measures that are frequently used as outcomes of interest predicted by various family circumstances and as predictors of children's cognitive and behavioral performance.

[40]The NLSY data also contain two additional maternal responses to low grades, namely, "punish child" and "limit non-school activities." We have excluded from the analysis the variable for punishment as it is difficult to objectively characterize this behavior as a driver of child development due to its possible detrimental effect, for example, through the disruption of the parent-child relationship. The variable for limitation of activities is not included as it was not asked in the first waves of the NLSY. Results remain similar if these two variables are also included in the analysis.

in parenting practices and quality of the parent-child interactions by estimating the same specification as in (9) with the cognitive stimulation score, the emotional support score, and maternal response to low grades as outcomes of interest. To ease the interpretation of the results, each outcome is standardized to obtain a measure with a mean of zero and a standard deviation of one and is expressed in first differences (difference between the current value and the value of the same variable from the previous survey wave).[41] Our analysis also takes into account that parenting practices might differ and produce differential effects depending on a child's age. The importance of considering a child's age follows the analysis of heterogeneous treatment effects.

Table 11 shows the estimated coefficients for a specification that includes the variable for policy-induced changes in EITC benefits ($\Delta EITC_{i,t}$) interacted with three indicator variables for a child's age. The first indicator is for children younger than eight, the second for those aged 9–11, and the third one is for children aged 12 or older. Each of these indicator variables for a child's age is also included in the regression. The table reports the analysis for both the specifications with and without state fixed effects.

The analysis points to vast heterogeneity by children's age and by parental input.[42] On the one hand, the cognitive stimulation score is quite similar across age groups and it is never significantly affected by EITC policy changes. On the other hand, the emotional support score is strongly negative and statistically significant for the group of children younger than 8: an increase of $1,000 in EITC benefits decreases the parental emotional support score by about 10 percent of a standard deviation. The effect is zero for older children. The results for maternal response to low grades is similar as a large negative effect (more than 20 percent of a standard deviation) arises for the younger age groups, and a zero effect is found for older children.

Table 12 investigate the possible link between the IV results on the income versus the substitution effect and the responsiveness of parental investments to the EITC expansion. We test whether a lower level of parental involvement is a direct consequence of EITC-induced increases in labor supply. Our specification in first differences estimates the effect of changes in maternal hours worked on changes in the cognitive stimulation score (columns 1 and 2), the emotional support score (columns 3 and 4), and maternal response to low grades

[41]For maternal response to low grades, each item is standardized to have a mean of zero and a standard deviation of one. Then, the items are aggregated in a comprehensive measure by computing the average of the seven standardized single items. Finally, the average is rescaled to have a mean of zero and a unitary standard deviation.

[42]The coefficients for the whole sample with no heterogenous effect by age are negative with estimates ranging between 1 and 2 percent of a standard deviation.

(columns 5 and 6). For each outcome, the first specification includes the usual set of control variables and the second one also includes state fixed effects. Maternal hours worked are treated as endogenous and instrumented with the variable for longitudinal changes in EITC benefits. Surges in maternal labor supply do not generate any increase in parental investments. Specifically, the table shows that an increase in hours worked leaves unaffected the cognitive stimulation score, while it causes a decrease in the emotional support score and in maternal response to low grades. This effect is sizable (6 to 11 percent of a standard deviation in response to a 100-hour increase) but, in line with previous results, only appears for children younger than eight.

In sum, the results in this section show no evidence of positive compensating behavior by parents due to their increased labor supply. This evidence is consistent with the results in Bastian and Lochner (2022), where the authors show that the increase in maternal work time associated with the EITC expansion decreased time with children but had no effect on educational activities. Our findings shed light on the quality of the parent-child interaction, and are aligned with the new evidence in Kalil et al. (2022) showing that the US welfare reform in the 1990s induced a decrease in the provision of maternal emotional support to their children. No effect is detected for cognitive-oriented activities. Similar to the conclusion suggested by the analysis of heterogeneous effects in Section 6.3, their analysis also suggests stronger negative effect for mothers with lower levels of human capital.

7.2 Female Labor Demand and Child Development

Throughout the paper we have provided evidence of the unintended consequences of EITC reforms on child development via labor supply adjustments. Here, we investigate whether similar labor supply effects arise for the case of shocks in local demand for female labor. Table 13 shows the effect of local demand for female labor on a child cognitive (columns 1 and 2), behavioral (columns 3 and 4), and development index (columns 5 and 6). For each outcome, we estimate a specification that includes the usual set of control variables and a second set augmented with state fixed effects.

The analysis depicts an insightful picture: surges in local demand for female labor do not generate any negative effect on short-term child development. An expansion in the labor market demand for mothers causes a boost in child cognitive development and has no detrimental impact on a child's behavioral development. Quantitatively, the analysis of cognitive development in columns (1) and (2) suggests that a 1 percent surge in the employment rate relative to 1980 induces a significant boost in the math-reading cognitive score of 6 to 12 percent of a standard deviation. The effect on behavioral development is also positive (about 1 percent of a standard deviation) but statistically nonsignificant. The positive effect of the female labor demand also arises in the analysis of the development index in the last two columns of the table. This evidence reassures of the fact that maternal hours worked do not necessarily harm a child's development.

How do we rationalize the opposite effects on child development of EITC-induced labor adjustments versus the ones implied by surges in local demand for maternal labor? Our theory of the income versus the substitution effect on child development helps answer this question. Indeed, changes in the local labor market conditions can generate higher returns to working hours, with local general equilibrium effects that can boost hourly wages for mothers. Conversely, the large increase in labor supply created by the EITC expansion can drive wages down (Rothstein, 2010). Under this hypothesis, the EITC expansion and shocks in female labor market demand can differentially affect child development because they differentially affect the change in disposable income per unit change of hours worked. The first-stage estimates in Table 6 confirm this intuition. Female labor demand shocks generate a change in disposable income per unit change of hours worked that is more than four times larger than the one generated by the EITC expansion.[43]

8 Conclusion

Workfare programs like the EITC, which have been proven to successfully incentivize work and to improve the economic conditions of low-income families, can create a natural trade-off between working and parenting. This is especially relevant for the most disadvantaged families, who have limited access to high-quality alternative child development inputs.

In this paper, we provide empirical evidence of this trade-off. Our results show that children from disadvantaged families experienced some losses in their short-term cognitive development and even higher losses in behavioral development in the aftermath of the EITC expansion in the 1990s. We reconcile these unintended consequences of the policy with a theory-driven empirical analysis of the trade-off between the *income* effect (economic resources) and the *substitution* effect (quantity and quality of the parent-child interactions) on

[43]This value is calculated, in the most general specification with state fixed effects, through the ratio of the ratios of the two first-stage coefficients for each instrument (Table 6), namely $\frac{(3.90/0.95)}{(1.87/2.22)}$.

the development of a child.

Our results highlight that optimal policies that aim to promote human capital in children from disadvantaged backgrounds should differ from standard means-tested transfer programs. For example, more effective programs could targeted disadvantaged children directly and engage their parents in the process of child development (Fryer et al., 2015; Zhou et al., 2021; Heckman and Zhou, 2021; Agostinelli et al., 2022). The evidence of the effectiveness of these type of programs, for example, home visits and mentoring programs in school, is substantial; see Heckman and Mosso (2014) for an exhaustive review. Moreover, promoting access to alternative high-quality childcare or after-school programs for disadvantaged children could also mitigate the money versus time trade-offs for child development. However, the positive impact on child development of programs such as formal childcare should not be taken for granted. Indeed, studies such as Baker et al. (2008), Morando and Platt (2022), and Houmark et al. (2022) show possible negative effects of formal childcare especially in terms of a child's noncognitive development. Finally, we also show that positive demand shocks for female labor in the 1990s—likely driven by technological progress and changes in labor productivity—do not generate any negative effect on short-term child development, despite predicting positive changes in maternal labor supply. Therefore, policies aimed at enhancing labor market returns and productivity can also succeed in supporting working mothers and their children. While this research highlights important trade-offs on child development induced by work-promoting income transfer policies, several questions on how to optimally design policies able to contemporaneously foster child development and maternal active labor force participation remain unanswered. We believe these represent interesting and policy-relevant questions for future research on child development.

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Table 1: Summary Statistics

Panel A	Math-Reading Sample		Behavior Problems Index Sample	
	Mean (1)	St.Dev. (2)	Mean (3)	St.Dev. (4)
Math-Reading	44.21	13.31	41.48	14.91
Behavior Problems Index	3.20	1.14	3.21	1.14
Family income	33,995	22,182	34,371	22,631
Hours worked (yearly)	1,265	985	1,246	982
Age	10.71	2.31	10.14	2.57
Male	0.50	0.50	0.50	0.50
White	0.45	0.50	0.46	0.50
Black	0.34	0.48	0.33	0.47
Hispanic	0.21	0.41	0.21	0.41
No siblings	0.09	0.29	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	0.62	0.48	0.64	0.48
Mother's education:				
High school dropout	0.22	0.42	0.21	0.41
High school graduate	0.51	0.50	0.51	0.50
Some college	0.21	0.40	0.21	0.41
Graduated college	0.06	0.24	0.07	0.25
Observations	11,089		12,357	

(continued...)

Table 1: Summary Statistics (continued)

Panel B	Math-Reading Sample				Behavior Problems Sample			
Year	Number of Children (1)	Fraction of Children Exposed to EITC (2)	Fraction of Children in EITC-eligible Families (3)	Hours Worked (yearly) (4)	Number of Children (5)	Fraction of Children Exposed to EITC (6)	Fraction of Children in EITC-eligible Families (7)	Hours Worked (yearly) (8)
1988	1,532	0.51	0.29	1,026	1,885	0.50	0.27	985
1990	1,532	0.53	0.35	1,126	1,885	0.52	0.34	1,087
1992	2,064	0.51	0.31	1,114	2,480	0.49	0.31	1,117
1994	2,094	0.50	0.35	1,223	2,431	0.49	0.33	1,198
1996	2,201	0.47	0.35	1,316	2,321	0.45	0.33	1,321
1998	1,880	0.44	0.34	1,382	1,899	0.43	0.34	1,387
2000	1,318	0.42	0.35	1,477	1,341	0.41	0.34	1,461
Whole Sample	12,621	0.48	0.34	1,236	14,242	0.47	0.32	1,211

This table shows the summary statistics of our estimating samples. In Panel A, 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. Panel B provides the descriptive statistics of the sample by year, that is, NLSY survey year. The unit of observation is the child. In Panel B, columns (1) to (4) refer to the estimating sample for the analysis of child cognitive development (combined Math-Reading test score). Columns (5) to (8) consider the estimating sample for the analysis of child behavioral development (Behavior Problems Index, BPI). Children exposed to the EITC represent the sample of children from mothers who are either eligible for EITC or that do not work (but are potentially subject to the incentives to work created by the EITC reform). Children in EITC-eligible families are in families receiving EITC benefits.

Table 2: EITC Expansion and Child Development

	(1) Math-Reading	(2) Math-Reading	(3) BPI	(4) BPI	(5) Develop. Index	(6) Develop. Index
Δ EITC	-0.03	-0.02	-0.05	-0.05	-0.05	-0.04
	[0.01]	[0.08]	[0.00]	[0.00]	[0.00]	[0.00]
Observations	11,089	11,089	12,357	12,357	9,660	9,660
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes

This table shows the reduced-form estimates for the effect of EITC policy changes on child development. Dependent variables: change in the Math-Reading test score (columns 1 and 2), change in the Behavior Problems Index (columns 3 and 4), and change in the development index (columns 5 and 6). Columns (1), (3), and (5) refer to the specification with control variables for changes in local demand for female labor, child's gender, age, and race, the number of children in the household, year, and the set of controls for family income trends. Columns (2), (4), and (6) refer to the same specification augmented with state fixed effects. EITC benefits are measured in $1,000 of year 2000 dollars. See text for further details. Resample-based p-values calculated with a nonparametric bootstrap algorithm clustered at the family level are reported in square brackets.

Table 3: EITC Expansion and Child Development: Robustness Tests

	(1) Math-Reading	(2) Math-Reading	(3) BPI	(4) BPI	(5) Develop. Index	(6) Develop. Index
Panel A: Controlling for Lagged Income $t-2$						
Δ EITC	-0.02	-0.02	-0.05	-0.06	-0.04	-0.05
	[0.05]	[0.06]	[0.00]	[0.01]	[0.00]	[0.00]
Observations	10,992	6,449	12,233	7,054	9,574	5,526
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Income $t-2$	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Whole	I<35K	Whole	I<35K	Whole	I<35K
Panel B: Controlling for Lagged Income $t-3$						
Δ EITC	-0.04	-0.04	-0.04	-0.05	-0.04	-0.05
	[0.00]	[0.00]	[0.02]	[0.02]	[0.00]	[0.00]
Observations	10,266	5,924	11,404	6,454	8,938	5,070
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Income $t-3$	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Whole	I<35K	Whole	I<35K	Whole	I<35K

This table shows the reduced-form estimates for the effect of EITC policy changes on child development by augmenting the specification with additional controls for lagged family income. Dependent variables: change in the Math-Reading test score (columns 1 and 2), change in the Behavior Problems Index (columns 3 and 4), and change in the development index (columns 5 and 6). Columns (1), (3), and (5) refer to the specification with control variables for changes in local demand for female labor, child's gender, age, and race, the number of children in the household, year, the set of controls for family income trends, and control variables for lagged family income. Columns (2), (4), and (6) refer to the same specification and to the restricted sample of families with initial income at $(t-1)$ below \$35,000. Panel A includes control variables for four-year lagged family income (two periods, $t-2$). Panel B includes control variables for six-year lagged family income (three periods, $t-3$). EITC benefits are measured in \$1,000 of year 2000 dollars. See text for further details. Resample-based p-values calculated with a nonparametric bootstrap algorithm clustered at the family level are reported in square brackets.

Table 4: Comparison with Dahl and Lochner (2012)

	(1) Math-Reading	(2) Math-Reading
Δ EITC	-0.03	0.04
	[0.01]	[0.09]
Observations	11,089	8,581
Controls	Yes	Yes
Framework	AS 2022	DL 2012

This table shows the reduced-form estimates for the effect of EITC policy changes on child development in our (labeled as AS 2022) and in Dahl and Lochner (2012, labeled as DL 2012) frameworks. Dependent variable: change in the Math-Reading test score. Column (1) replicates the model in Table 2, column (1). Column (2) includes control variables for child's gender, age, and race, the number of children in the household, an indicator variable for positive lagged pre-tax income, and a fifth-order polynomial in lagged pre-tax income. EITC benefits are measured in $1,000 of year 2000 dollars. See text for further details. Resample-based p-values calculated with a nonparametric bootstrap algorithm clustered at the family level are reported in square brackets in column (1). Family-level clustered p-values are reported in square brackets in column (2).

Table 5: Maximum EITC and Child Development

	(1) Math-Reading	(2) Math-Reading	(3) Math-Reading	(4) BPI	(5) BPI	(6) BPI	(7) Develop. Index	(8) Develop. Index	(9) Develop. Index
Δ MaxEITC	-0.03	-0.03	-0.02	-0.03	-0.03	-0.06	-0.04	-0.04	-0.04
	[0.02]	[0.01]	[0.23]	[0.02]	[0.03]	[0.01]	[0.00]	[0.00]	[0.01]
Observations	11,089	10,992	6,449	12,357	12,233	7,054	9,660	9,574	5,526
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Child Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DepChXYear	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
StateXYear	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Child AgeXYear	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Income	No	Yes	No	No	Yes	No	No	Yes	No
Sample	Whole	Whole	I<35K	Whole	Whole	I<35K	Whole	Whole	I<35K

This table shows the reduced-form estimates for the effect of changes in the maximum federal and state EITC benefits on child development. Dependent variables: change in the Math-Reading test score (columns 1 to 3), change in the Behavior Problems Index (columns 4 to 6), and change in the development index (columns 7 to 9). All specifications include control variables for changes in local demand for female labor, child's gender, age, and race, the number of children in the household, and year. All specifications also include interaction terms between state (indicators) and year, the number of dependent children (indicators) and year, and the child's age (indicators) and year. Columns (1), (4), and (7) refer to the whole sample. Columns (2), (5), and (8) refer to the whole sample and are augmented with a control variable for four-year lagged family income. Columns (3), (6), and (9) refer to the restricted sample of families with initial income at $(t-1)$ below \$35,000. The maximum federal and state EITC benefits are measured in \$1,000 of year 2000 dollars. See text for further details. Family-level clustered p-values are reported in square brackets.

Table 6: Instrumental Variables: First-Stage Estimates

	(1) Δ Income	(2) Δ Hours	(3) Δ Income	(4) Δ Hours
Δ EITC	1.58	2.12	1.87	2.22
	[0.00]	[0.00]	[0.00]	[0.00]
Lab.Dem.Shocks	1.85	0.43	3.90	0.95
	[0.00]	[0.00]	[0.00]	[0.00]
Observations	11,089	11,089	11,089	11,089
Controls	Yes	Yes	Yes	Yes
State FE	No	No	Yes	Yes
F	17.37	38.42	27.09	42.91
SW Chi-sq (Under id)	19.85	24.94	34.04	40.08
SW F (Weak id)	19.82	24.90	33.83	39.83
KP (Weak id)	9.97	9.97	17.32	17.32

This table shows the first-stage estimates for the IV analysis. Dependent variables: change in family income (ΔIncome, columns 1 and 3) and change in maternal labor supply (ΔHours, columns 2 and 4). The two instrumental variables are: changes in EITC benefits (Δ EITC) and labor demand shocks (Lab.Dem.Shocks). Columns (1) and (2) refer to the specification with control variables for child's gender, age, and race, the number of children in the household, year, and the set of controls for family income trends. Columns (3) and (4) refer to the same specification augmented with state fixed effects. Income and EITC benefits are measured in $1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. The analysis refers to the estimating sample for the analysis of child cognitive development (Math-Reading test score). See text for further details. Resample-based p-values calculated with a nonparametric bootstrap algorithm clustered at the family level are reported in square brackets. Diagnostic tests for first-stage models reported in the bottom part of the table are obtained through the Stata command *ivreg2*.

Table 7: Instrumental Variables: Income, Hours Worked, and Child Development

	(1) Math-Reading	(2) Math-Reading	(3) BPI	(4) BPI	(5) Develop. Index	(6) Develop. Index
Δ Income	0.04	0.04	0.01	0.01	0.03	0.02
	[0.00]	[0.00]	[0.09]	[0.10]	[0.00]	[0.00]
Δ Hours	-0.05	-0.04	-0.03	-0.03	-0.04	-0.04
	[0.01]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Observations	11,089	11,089	12,357	12,357	9,660	9,660
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes

This table shows the IV analysis for the effect of changes in family income and maternal labor supply on child development. Dependent variables: change in the Math-Reading test score (columns 1 and 2), change in the Behavior Problems Index (columns 3 and 4), and change in the development index (columns 5 and 6). The two instrumental variables are: changes in EITC benefits (Δ EITC) and labor demand shocks (Lab.Dem.Shocks). Columns (1), (3), and (5) refer to the specification with control variables for child's gender, age, and race, the number of children in the household, year, and the set of controls for family income trends. Columns (2), (4), and (6) refer to the same specification augmented with state fixed effects. Income is measured in $1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. See text for further details. Resample-based p-values calculated with a nonparametric bootstrap algorithm clustered at the family level are reported in square brackets.

Table 8: Instrumental Variables: Robustness Tests

	(1) Math-Reading	(2) Math-Reading	(3) BPI	(4) BPI	(5) Develop. Index	(6) Develop. Index
Panel A: Controlling for Lagged Income $t-2$						
Δ Income	0.05	0.05	0.01	0.01	0.03	0.03
	[0.00]	[0.04]	[0.07]	[0.43]	[0.01]	[0.02]
Δ Hours	-0.06	-0.06	-0.04	-0.04	-0.06	-0.05
	[0.03]	[0.05]	[0.01]	[0.01]	[0.01]	[0.04]
Observations	10,992	6,449	12,233	7,054	9,574	5,526
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Income $t-2$	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Whole	I<35K	Whole	I<35K	Whole	I<35K
Panel B: Controlling for Lagged Income $t-3$						
Δ Income	0.07	0.07	0.01	0.01	0.04	0.03
	[0.02]	[0.06]	[0.14]	[0.39]	[0.03]	[0.05]
Δ Hours	-0.07	-0.07	-0.02	-0.03	-0.05	-0.05
	[0.02]	[0.03]	[0.01]	[0.02]	[0.00]	[0.01]
Observations	10,266	5,924	11,404	6,454	8,938	5,070
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Income $t-3$	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Whole	I<35K	Whole	I<35K	Whole	I<35K

This table shows the IV analysis for the effect of changes in family income and maternal labor supply on child development by augmenting the specification with additional controls for lagged family income. Dependent variables: change in the Math-Reading test score (columns 1 and 2), change in the Behavior Problems Index (columns 3 and 4), and change in the development index (columns 5 and 6). The two instrumental variables are: changes in EITC benefits (Δ EITC) and labor demand shocks (Lab.Dem.Shocks). Columns (1), (3), and (5) refer to the specification with control variables for child's gender, age, and race, the number of children in the household, year, the set of controls for family income trends, and control variables for lagged family income. Columns (2), (4), and (6) refer to the same specification and to the restricted sample of families with initial income at $(t-1)$ below \$35,000. Panel A includes control variables for four-year lagged family income (two periods, $t-2$). Panel B includes control variables for six-year lagged family income (three periods, $t-3$). Income is measured in \$1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. See text for further details. Resample-based p-values calculated with a nonparametric bootstrap algorithm clustered at the family level are reported in square brackets.

Table 9: EITC Expansion and Child Development: Effect Heterogeneity

	(1) Math-Reading	(2) Math-Reading	(3) Math-Reading	(4) Math-Reading	(5) BPI	(6) BPI	(7) BPI	(8) BPI
				Mother's Education				
Δ EITC	-0.03	-0.02	0.01	0.01	-0.05	-0.06	-0.05	-0.05
	[0.02]	[0.05]	[0.68]	[0.77]	[0.02]	[0.01]	[0.07]	[0.11]
Observations	8,105	8,105	2,984	2,984	8,943	8,943	3,414	3,414
Sample	Low Ed.	Low Ed.	High Ed.	High Ed.	Low Ed.	Low Ed.	High Ed.	High Ed.
				Mother's Marital Status				
Δ EITC	0.05	0.05	-0.05	-0.03	-0.08	-0.07	-0.05	-0.06
	[0.06]	[0.06]	[0.00]	[0.00]	[0.05]	[0.07]	[0.00]	[0.00]
Observations	6,927	6,927	4,162	4,162	7,862	7,862	4,495	4,495
Sample	Married	Married	Unmarried	Unmarried	Married	Married	Unmarried	Unmarried
				Child's Age				
Δ EITC	-0.05	-0.04	-0.01	-0.00	-0.07	-0.07	-0.03	-0.03
	[0.00]	[0.01]	[0.59]	[0.99]	[0.00]	[0.00]	[0.17]	[0.29]
Observations	6,838	6,838	4,251	4,251	8,342	8,342	4,015	4,015
Sample	Below 12	Below 12	Above 12	Above 12	Below 12	Below 12	Above 12	Above 12
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes	No	Yes

This table shows the heterogeneity in the reduced-form estimates for the effect of EITC policy changes on child development. Dependent variables: change in the Math-Reading test score (columns 1 to 4) and change in the Behavior Problems Index (columns 4 to 8). The following sources of heterogeneity are investigated: (i) mother's educational attainment (Low Education: high school diploma or less; High Education: some college or more); (ii) mother's marital status (Married; Unmarried); and (iii) child's age (Below 12; Above 12). Columns (1), (3), (5), and (7) refer to the specification with control variables for changes in local demand for female labor, child's gender, age, and race, the number of children in the household, year, and the set of controls for family income trends. Columns (2), (4), (6), and (8) refer to the same specification augmented with state fixed effects. EITC benefits are measured in \$1,000 of year 2000 dollars. See text for further details. Resample-based p-values calculated with a nonparametric bootstrap algorithm clustered at the family level are reported in square brackets.

Table 10: Instrumental Variable and Effect Heterogeneity

	(1) Math-Reading	(2) Math-Reading	(3) BPI	(4) BPI
	Mother's Education			
Δ Income*Low Ed.	0.03	0.03	0.01	0.00
	[0.00]	[0.00]	[0.21]	[0.83]
Δ Income*High Ed.	0.04	0.04	0.01	0.01
	[0.00]	[0.00]	[0.29]	[0.07]
Δ Hours*Low Ed.	-0.04	-0.03	-0.03	-0.03
	[0.00]	[0.00]	[0.01]	[0.01]
Δ Hours*High Ed.	-0.02	-0.03	-0.03	-0.03
	[0.19]	[0.01]	[0.10]	[0.03]
	Mother's Marital Status			
Δ Income*Married	0.04	0.04	0.01	0.01
	[0.00]	[0.00]	[0.09]	[0.13]
Δ Income*Unmarried	0.04	0.04	0.01	0.01
	[0.00]	[0.00]	[0.21]	[0.22]
Δ Hours*Married	-0.02	-0.02	-0.05	-0.04
	[0.47]	[0.35]	[0.01]	[0.02]
Δ Hours*Unmarried	-0.05	-0.05	-0.03	-0.03
	[0.00]	[0.00]	[0.00]	[0.01]
	Child's Age			
Δ Income*Below 12	0.05	0.04	0.01	0.01
	[0.00]	[0.00]	[0.03]	[0.25]
Δ Income*Above 12	0.03	0.04	0.00	0.01
	[0.01]	[0.00]	[0.94]	[0.15]
Δ Hours*Below 12	-0.06	-0.05	-0.04	-0.03
	[0.00]	[0.00]	[0.00]	[0.00]
Δ Hours*Above 12	-0.02	-0.03	-0.03	-0.04
	[0.20]	[0.00]	[0.16]	[0.01]
Observations	11,089	11,089	12,357	12,357
Controls	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes

This table shows the heterogeneity in the IV estimates for the effect of changes in family income and maternal labor supply on child development. Dependent variables: change in the Math-Reading test score (columns 1 and 2) and change in the Behavior Problems Index (columns 3 and 4). The following sources of heterogeneity are investigated: (i) mother's educational attainment (Low Education: high school diploma or less; High Education: some college or more); (ii) mother's marital status (Married; Unmarried); and (iii) child's age (Below 12; Above 12). The two instrumental variables are: changes in EITC benefits (Δ EITC) and labor demand shocks (Lab.Dem.Shocks). Columns (1) and (3) refer to the specification with control variables for child's gender, age, and race, the number of children in the household, year, and the set of controls for family income trends. Columns (2) and (4) refer to the same specification augmented with state fixed effects. Income is measured in \$1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. Standard errors are obtained through a family-level clustered bootstrap procedure based on 100 repetitions. See text for further details. Resample-based p-values calculated with a nonparametric bootstrap algorithm clustered at the family level are reported in square brackets.

Table 11: EITC Expansion and Parental Inputs

	(1) Cognitive Stimulation	(2) Cognitive Stimulation	(3) Emotional Support	(4) Emotional Support	(5) Response Low Grades	(6) Response Low Grades
Δ EITC*Age≤8	-0.02	-0.01	-0.11	-0.10	-0.23	-0.22
	[0.35]	[0.78]	[0.00]	[0.00]	[0.01]	[0.01]
Δ EITC*Age9-11	-0.02	-0.01	0.02	0.02	-0.02	-0.01
	[0.32]	[0.56]	[0.56]	[0.39]	[0.66]	[0.68]
Δ EITC*Age≥12	-0.01	-0.00	0.01	0.01	0.02	0.02
	[0.58]	[0.93]	[0.76]	[0.62]	[0.58]	[0.59]
Observations	10,868	10,868	9,968	9,968	9,189	9,189
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes

This table shows the reduced-form estimates by child's age for the effect of EITC policy changes on changes in parental investment and behavior. Dependent variables: change in the cognitive stimulation score (columns 1 and 2), change in the emotional support (columns 3 and 4), and change in maternal response to low grades (columns 5 and 6). Columns (1), (3), and (5) refer to the specification with control variables for changes in local demand for female labor, age groups (indicators), child's gender, age, and race, the number of children in the household, year, and the set of controls for family income trends. Columns (2), (4), and (6) refer to the same specification augmented with state fixed effects. EITC benefits are measured in \$1,000 of year 2000 dollars. See text for further details. Resample-based p-values calculated with a nonparametric bootstrap algorithm clustered at the family level are reported in square brackets.

Table 12: Instrumental Variables: Parental Inputs and Hours Worked

	(1) Cognitive Stimulation	(2) Cognitive Stimulation	(3) Emotional Support	(4) Emotional Support	(5) Response Low Grades	(6) Response Low Grades
Δ Hours*Age≤8	-0.01	-0.01	-0.07	-0.06	-0.11	-0.11
	[0.41]	[0.78]	[0.01]	[0.01]	[0.04]	[0.03]
Δ Hours*Age9-11	-0.01	-0.01	0.01	0.02	-0.01	-0.01
	[0.40]	[0.51]	[0.35]	[0.28]	[0.56]	[0.59]
Δ Hours*Age≥12	-0.00	-0.00	0.01	0.01	0.01	0.01
	[0.70]	[0.86]	[0.65]	[0.55]	[0.52]	[0.52]
Observations	10,868	10,868	9,968	9,968	9,189	9,189
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes

This table shows the IV analysis by child's age for the effect of changes maternal labor supply on changes in parental investment and behavior. Dependent variables: change in the cognitive stimulation score (columns 1 and 2), change in the emotional support (columns 3 and 4), and change in maternal response to low grades (columns 5 and 6). The instrumental variables are: changes in EITC benefits (Δ EITC) interacted with age groups (indicators). Columns (1), (3), and (5) refer to the specification with control variables for age groups (indicators), child's gender, age, and race, the number of children in the household, year, and the set of controls for family income trends. Columns (2), (4), and (6) refer to the same specification augmented with state fixed effects. Hours worked are yearly hours and expressed in hundreds. See text for further details. Resample-based p-values calculated with a nonparametric bootstrap algorithm clustered at the family level are reported in square brackets.

Table 13: Female Labor Demand Shocks and Child Development

	(1) Math-Reading	(2) Math-Reading	(3) BPI	(4) BPI	(5) Develop. Index	(6) Develop. Index
Lab.Dem.Shocks	0.06	0.12	0.01	0.01	0.03	0.07
	[0.00]	[0.00]	[0.37]	[0.51]	[0.00]	[0.00]
Observations	11,089	11,089	12,357	12,357	9,660	9,660
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes

This table shows the reduced-form estimates for the effect of changes in local demand for female labor on child development. Dependent variables: change in the Math-Reading test score (columns 1 and 2), change in the Behavior Problems Index (columns 3 and 4), and change in the development index (columns 5 and 6). Columns (1), (3), and (5) refer to the specification with control variables for EITC policy changes, child's gender, age, and race, the number of children in the household, year, and the set of controls for family income trends. Columns (2), (4), and (6) refer to the same specification augmented with state fixed effects. See text for further details. Resample-based p-values calculated with a nonparametric bootstrap algorithm clustered at the family level are reported in square brackets.

Appendix A: Additional Tables and Figures

Table A.1: Maximum EITC and Child Development: Restricted Sample

	(1) Math-Reading	(2) Math-Reading	(3) Math-Reading	(4) BPI	(5) BPI	(6) BPI	(7) Develop. Index	(8) Develop. Index	(9) Develop. Index
Δ MaxEITC	-0.02	-0.02	-0.02	-0.04	-0.03	-0.06	-0.03	-0.03	-0.04
	[0.07]	[0.07]	[0.22]	[0.04]	[0.04]	[0.02]	[0.02]	[0.02]	[0.04]
Observations	9,659	9,569	5,637	10,666	10,557	6,123	8,416	8,336	4,821
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Child Age FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
DepChXYear	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
StateXYear	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Child AgeXYear	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Lagged Income	No	Yes	No	No	Yes	No	No	Yes	No
Sample	Whole	Whole	I<35K	Whole	Whole	I<35K	Whole	Whole	I<35K

This table replicates the reduced-form estimates in Table 5 for a restricted sample of mothers who did not change either their state of residence or the number of children in two consecutive NLSY surveys. The table shows the reduced-form estimates for the effect of changes in the maximum federal and state EITC benefits on child development. Dependent variables: change in the Math-Reading test score (columns 1 to 3), change in the Behavior Problems Index (columns 4 to 6), and change in the development index (columns 7 to 9). All specifications include control variables for changes in local demand for female labor, child's gender, age, and race, the number of children in the household, and year. All specifications also include interaction terms between state (indicators) and year, the number of dependent children (indicators) and year, and child's age (indicators) and year. Columns (1), (4), and (7) refer to the whole sample. Columns (2), (5), and (8) refer to the whole sample and are augmented with a control variable for four-year lagged family income. Columns (3), (6), and (9) refer to the restricted sample of families with initial income at $(t-1)$ below \$35,000. The maximum federal and state EITC benefits are measured in \$1,000 of year 2000 dollars. See text for further details. Family-level clustered p-values are reported in square brackets.

Table A.2: Maximum EITC and Child Development: Cross-Section vs Longitudinal

	(1) Math-Reading (Level)	(2) Math-Reading (Δ)	(3) BPI (Level)	(4) BPI (Δ)	(5) Develop. Index (Level)	(6) Develop. Index (Δ)
MaxEITC	0.03		0.08		0.06	
	[0.10]		[0.00]		[0.02]	
Δ MaxEITC		-0.03		-0.03		-0.04
		[0.02]		[0.02]		[0.00]
Observations	11,089	11,089	12,357	12,357	9,660	9,660
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Child Age FE	Yes	Yes	Yes	Yes	Yes	Yes
DepChXYear	Yes	Yes	Yes	Yes	Yes	Yes
StateXYear	Yes	Yes	Yes	Yes	Yes	Yes
Child AgeXYear	Yes	Yes	Yes	Yes	Yes	Yes
Specification	Level	Delta	Level	Delta	Level	Delta

This table shows the reduced-form estimates (in level and in first differences) for the effect of (changes in) the maximum federal and state EITC benefits on child development. Dependent variables: Math-Reading test score (column 1), change in the Math-Reading test score (column 2), Behavior Problem Index (column 3), change in the Behavior Problems Index (column 4), development index (column 5), and change in the development index (column 6). All specifications include control variables for changes in local demand for female labor, child's gender, age, and race, the number of children in the household, and year. All specifications also include interaction terms between state (indicators) and year, the number of dependent children (indicators) and year, and child's age (indicators) and year. The maximum federal and state EITC benefits are measured in $1,000 of year 2000 dollars. See text for further details. Family-level clustered p-values are reported in square brackets.

Table A.3: Instrumental Variables: First-Stage Estimates by Sample

	(1) Δ Income	(2) Δ Hours	(3) Δ Income	(4) Δ Hours	(5) Δ Income	(6) Δ Hours	(7) Δ Income	(8) Δ Hours
Δ EITC	1.39	2.07	1.68	2.16	1.71	2.14	2.02	2.22
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Lab.Dem.Shocks	2.29	0.36	4.27	0.67	2.06	0.42	4.31	0.82
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Observations	12,357	12,357	12,357	12,357	9,660	9,660	9,660	9,660
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	No	Yes	Yes	No	No	Yes	Yes
Sample	BPI	BPI	BPI	BPI	Develop. Index	Develop. Index	Develop. Index	Develop. Index
F	20.92	36.15	29.56	38.86	17.24	33.59	26.45	36.42
SW Chi-sq (Under id)	34.42	44.88	49.72	57.07	21.91	26.32	37.95	41.74
SW F (Weak id)	34.37	44.81	49.44	56.75	21.87	26.27	37.69	41.45
KP (Weak id)	17.45	17.45	25.80	25.80	10.98	10.98	19.21	19.21

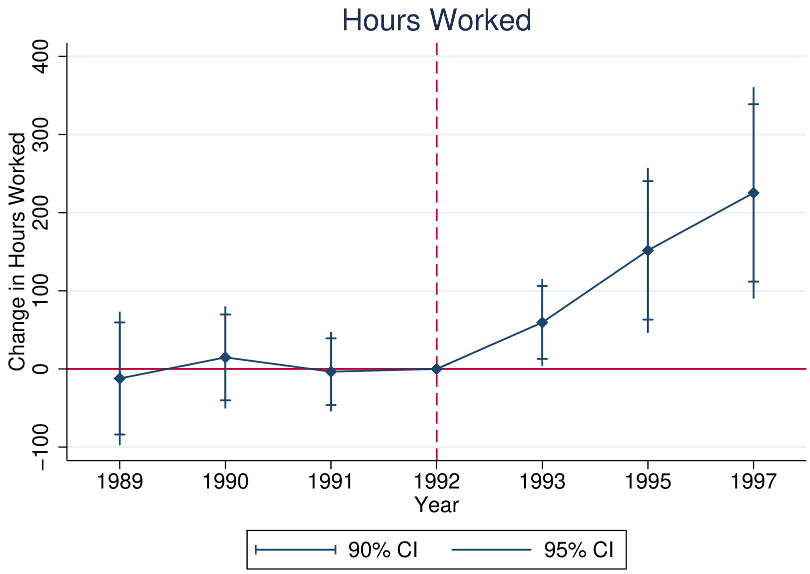
This table shows the first-stage estimates for the IV analysis. Dependent variables: change in family income (ΔIncome, columns 1, 3, 5, and 7) and change in maternal labor supply (ΔHours, columns 2, 4, 6, and 8). The two instrumental variables are: changes in EITC benefits (Δ EITC) and labor demand shocks (Lab.Dem.Shocks). Columns (1)–(2) and (5)–(6) refer to the specification with control variables for child's gender, age, and race, the number of children in the household, year, and the set of controls for family income trends. Columns (3)–(4) and (7)–(8) refer to the same specification augmented with state fixed effects. Income and EITC benefits are measured in $1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. The analysis in columns (1)–(4) refers to the estimating sample for the analysis of child behavioral development (BPI). The analysis in columns (5)–(8) refers to the estimating sample for the analysis of child development index. See text for further details. Resample-based p-values calculated with a nonparametric bootstrap algorithm clustered at the family level are reported in square brackets. Diagnostic tests for first-stage models reported in the bottom part of the table are obtained through the Stata command *ivreg2*.

Table A.4: Instrumental Variables: Family's Hours Worked

	(1) Math-Reading	(2) Math-Reading	(3) BPI	(4) BPI	(5) Develop. Index	(6) Develop. Index
Δ Income	0.05	0.05	0.01	0.01	0.03	0.03
	[0.00]	[0.00]	[0.02]	[0.02]	[0.01]	[0.00]
Δ Hours Family	-0.04	-0.04	-0.03	-0.03	-0.04	-0.04
	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.00]
Observations	11,089	11,089	12,357	12,357	9,660	9,660
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	No	Yes	No	Yes	No	Yes

This table shows the IV analysis for the effect of changes in family income and labor supply (family level) on child development. Dependent variables: change in the Math-Reading test score (columns 1 and 2), change in the Behavior Problems Index (columns 3 and 4), and change in the development index (columns 5 and 6). The two instrumental variables are: changes in EITC benefits (Δ EITC) and labor demand shocks (Lab.Dem.Shocks). Columns (1), (3), and (5) refer to the specification with control variables for child's gender, age, race, the number of children in the household, year, and the set of controls for family income trends. Columns (2), (4), and (6) refer to the same specification augmented with state fixed effects. Income is measured in $1,000 of year 2000 dollars. Hours worked are yearly hours and expressed in hundreds. See text for further details. Resample-based p-values calculated with a nonparametric bootstrap algorithm clustered at the family level are reported in square brackets.

Figure A.1: The 1993 EITC Reform and Maternal Labor Supply: Additional Controls



This figure shows the evolution over time of the effect of exposure to the EITC program on maternal labor supply. Dependent variable: change in maternal labor supply (in hours worked per year). The y-axis shows the point estimates for the interaction of the indicator variable for the treatment group with indicator variables for each year. The treatment group is defined as the group of families that received EITC benefits at least once pre-1993 or those with members that never worked before the reform. The x-axis reports years. The red, vertical, dashed line visually separates the pre-reform and the post-reform periods. The model includes control variables for a child's race and number of children in the household. The model also includes control variables for state welfare waivers and unemployment level. Each control variable is also interacted with the indicator variable for the treatment group. See text for further details. The figure reports 90 percent and 95 percent confidence intervals based on standard errors clustered at the family level.