Intra-Household Insurance and the Intergenerational Transmission of Income Risk

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Abstract

This paper studies the mechanisms and the extent to which parental wage risk passes through to children's skill development. Through a quantitative dynamic labor supply model in which two parents choose whether to work short or long hours or not work at all, time spent with children, and child-related expenditures, we find that income risk impacts skill accumulation, permanently lowering children's skill levels. To the extent that making up for cognitive skill losses during childhood is hard—as available evidence suggests—uninsurable income risk can negatively impact the labor market prospects of future generations.

Keywords: Wage risk; Household labor supply; Income taxation; Child development; Social insurance.

JEL Classification: D1; H24; J13; J22.

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1. Introduction

Prominent and influential literature highlights the critical role of parental investment in the early stages of childhood for the development of children's skills (see Heckman and Mosso, 2014, for a comprehensive literature review). Because of dynamic complementarity in skill accumulation, the return to parental investment is high early when the child begins acquiring critical cognitive skills. An implication of this theory, hitherto unexplored, is that uninsurable parental income risk can significantly alter how parents allocate time and resources within the family, affecting their children's skill accumulation path. For example, a temporary reduction in family earnings may induce parents to work more, thus subtracting time allocated to their child. To the extent that parental time investment is valuable in producing children's skills, and the adverse earning shock occurs early on in the child's life, life-cycle wage risk can pass through to children. Whether later investments can make up for earlier skill losses critically depends on the degree of dynamic complementarity in skill accumulation. Uninsurable idiosyncratic risk can have a "scarring effect" that permanently reduces children's skill accumulation path.

In this paper, we study how and the extent to which idiosyncratic wage risk of parents affects the intra-household allocation of time and resources, parental investment decisions, and, thereby, children's skill levels. In an ideal world with perfect insurance markets, parents could hedge parental investments in children's skills so that skill development would be, to a large extent, insulated from idiosyncratic risk. However, it is well-known that households face a nontrivial amount of uninsurable risk (Guiso, Jappelli, and Pistaferri, 2002; Blundell, Pistaferri, and Preston, 2008; Heathcote, Storesletten, and Violante, 2014; Jappelli and Pistaferri, 2010; Low, Meghir, and Pistaferri, 2010; Arellano, Blundell, and Bonhomme, 2017; De Nardi, Fella, and Paz-Pardo, 2019), and that the number of existing welfare programs can only partially insure households against lost income (Autor et al., 2019). Thus, the limited ability of families with children to smooth out temporary wage shocks is an essential and realistic aspect of understanding children's outcomes and policy evaluation.

We develop a two-parent life-cycle model of endogenous children's skill formation to study the intergenerational transmission of parental income risk. In the model, both parents make consumption and labor supply decisions in the face of uninsurable, idiosyncratic wage shocks. We model labor supply along the extensive margin, allowing for nonparticipation, part-time and full-time work. This three-state representation of the labor supply decision captures the well-documented discreteness of hours worked and earnings in the data (see, e.g., French, 2005; Bick, Blandin, and Rogerson, 2022; Rogerson, 2024). In the model, and consistently with US data, individuals do not choose from a continuous menu of hours-wage bundles; instead, each parent has a discrete choice between working short or long hours or not working at all.

Such discreetness in hours worked limits parents' ability to self-insure against wage shocks. Also, allowing for nonparticipation is critical to capture the observation that the female labor supply is quite elastic to changes in work incentives (Attanasio, Low, and Sánchez-Marcos, 2005; Attanasio et al., 2018).

The main idea in the model is that children's skills are exposed to parents' idiosyncratic wage risk. We assume that parents cannot borrow, as in Del Boca, Flinn, and Wiswall (2014), so labor supply is the only insurance mechanism at work in response to adverse wage shocks. Children's skills accumulate over childhood as a function of parental investment. In our context, investment in a child's skill development consists of time spent with the children, which varies by parent and child-related expenditures. The time dedicated to children is not perfectly substitutable with child-related expenditures and is jointly determined alongside both parents' labor market time allocations. Therefore, the opportunity cost of working extends beyond the standard foregone value of leisure, as discussed in Imai and Keane (2004).

To bring the model to the data, we combine moments from three datasets: the Consumer Expenditure Survey (CE), the American Time Use Survey (ATUS), the National Longitudinal Study of Youth 1979 (NLSY79), and the NLSY79 Children survey (NSLY79-C). These datasets provide information on labor market outcomes, time use, expenditures, wages, earnings, and children's test scores. More specifically, we require the model to reproduce the profile of children's skills (means and standard deviations), parents' accepted wages, earnings, and joint labor supply decisions by child's age. Further, to discipline the initial heterogeneity across families in terms of children's skills, we leverage the first available test scores (at age 5) and their correlation with the earnings of both parents. This ensures that our model accurately captures the initial heterogeneity in the joint distribution of children's cognitive skills and family income across different households.

Having established that the model replicates key facts of the data, we use it to conduct several quantitative experiments to quantify the pass-through of wage risk on children's skills. Three main results stand out: (1) We find that a mean-preserving spread of the wage offer distributions of both parents permanently reduces children's skill levels at age 14. To the extent that these skill gaps are challenging to close later in life, as the empirical evidence suggests, parental wage risk has scarring effects on children's skills. (2) Increasing fathers' wage risk has a more significant adverse effect on skill levels than increasing the wage risk of mothers. The transmission of wage risk to children's skills varies among families, and this heterogeneity is more pronounced when fathers' risk is heightened compared to mothers'. (3) When the wage risk shock hits both parents, we see a fall in average skill levels combined with increased skill dispersion that is larger than when wage risk rises for each parent in isolation. In this case, intra-household insurance via joint labor supply is limited since both mothers and fathers face higher earnings risk profiles over the child's age.

Turning to the transmission mechanism of income risk, we stress that disposable household income falls when the wage risk of each parent in isolation or both rises. This reduction in disposable income is associated with a sizable decrease in child-related expenditures, whereas household consumption remains virtually unchanged. Parents facing increased risk respond by smoothing the household's consumption at the expense of child-related expenditures. However, parents raise time spent with children to offset this reduction in child-related expenditures.

We find that within-family specialization by wage risk emerges as an endogenous outcome. As one parent's wage risk rises, the other parent specializes in market hours worked, while the "riskier" parent focuses on child-related time activities. This intra-household reallocation of time results from a self-insurance motive against wage risk and impacts child development. To sum up, life-cycle wage risk—possibly related to technological progress or structural transformation—can negatively impact child development.

Finally, we argue that public policies can mitigate these adverse consequences for the younger generation. More specifically, we evaluate the degree to which a more progressive tax system can alleviate the negative impact of income risk on children's skill accumulation. We find that they do. Through the standard insurance effect of progressive taxation, the heightened tax progressivity mitigates the transmission of increased wage risk across the board. This, in turn, diminishes the negative consequences for child development resulting from higher wage risk, particularly in the scenario of high life-cycle wage risk for fathers. We also investigate the effects of an unfunded Universal Basic Income (UBI) proposal to quantify the role of an income floor. Despite potential substitution effects between inputs in child development, our findings indicate that the policy enhances children's outcomes, particularly for the lower end of the income distribution. Interestingly, although we assume the UBI does not involve raising taxes nor redistributing resources from higher to lower-income families, our results show that a nonnegligible number of children from such families experience skill losses—such adverse effects result from input substitution in the child development process caused by the UBI policy.

We structure the paper as follows. In Section 2, we discuss our contribution to the literature. In Section 3, we begin with novel evidence on the impact of the Earned Income Tax Credit (EITC) program on parents' time allocations and child-related expenditures. In Section 4, we present the model. We parameterize the model in Section 5 and conduct quantitative experiments in Section 6. Section 7 concludes.

2. Related Literature

Our paper contributes to understanding how parents' decisions affect children's skills when faced with uninsurable wage risk. We take the view that parents are unique actors in the process of child development and that government policies can affect children's outcomes by leveraging the dynamic complementarities inherent to the children's skills development and accumulation process, starting at young ages (Heckman and Mosso, 2014).

Several recent studies, starting with the seminal work of Cunha, Heckman, and Schennach (2010), estimate the technology of children's skill formation (Agostinelli and Wiswall, 2016; Attanasio et al., 2020; Attanasio, Meghir, and Nix, 2020; Bolt et al., 2021, 2023; Caucutt et al., 2020; Del Boca et al., 2019). Estimates of such technology are paramount to any quantitative evaluation of policies directed to foster children's skill development. Literature has addressed several substantive questions related to the complementarity of the inputs in the production of children's skills, including the degree of dynamic complementarity and their relevance for policy, and the distinction between money and time as inputs into the technology of children's skill formation (see, for example, Løken, Mogstad, and Wiswall, 2012; Del Boca, Flinn, and Wiswall, 2014; Carneiro, Løken, and Salvanes, 2015; Caucutt and Lochner, 2020; Agostinelli and Sorrenti, 2022). However, to date, it has abstracted from risk-related issues and, more specifically, quantifying the extent to which tax-and-transfer systems can help households cope with such a risk. To our knowledge, this is the first paper to tackle this question.

Starting with the closely related papers, Del Boca, Flinn, and Wiswall (2014) estimate a model of two-parent household decisions with time and monetary investments in children and a Cobb-Douglas children's skill production function. Cobb-Douglas technology makes parent's decisions invariant to children's skills, downplaying the important role of dynamic complementarities between parents' actions and children's skill dynamics. Caucutt et al. (2020) quantify the degree of such complementarity in a two-parent household model with borrowing and saving subject to a borrowing constraint and a CES production function for children's skill formation. They present an ingenious estimation strategy that allows for estimating the parameters of the technology using solely intratemporal optimality conditions and finding that the extent of complementary between inputs in such technology is quantitatively crucial for policies affecting relative input prices.

With a focus on the policy impact on children's skills, Mullins (2022) studies the design of optimal social welfare programs in the US while accounting for the endogenous children's human capital costs and benefits of the policies. The paper finds that the optimal insurance policy should provide reduced work incentives for low-income families because of the associated costs for the skill development of disadvantaged children. Similarly, Bolt et al. (2023) build and estimate a model of child development in which both mothers and fathers invest in their children. This framework incorporates a linear skill production function where maternal and paternal time are perfect substitutes. Education subsidies can reduce inequality, capitalizing on the dynamic complementarity between time investments and education. Finally, Mullins (2020) leverages a child development model to aggregate a set of reduced-form local treatment effects from various welfare reform experiments. This exercise allows the author to identify the model's policy-relevant parameters, characterizing responses in labor supply, child care usage, and parental investments in child development.

Despite similarities, there are crucial differences between our work and these papers. Our paper addresses a different question, develops a new model, and sheds light on an overlooked mechanism. First, we focus on how parental earnings risk affects children's skills. Such pass-through can have permanent adverse effects on children's skill levels. In the model, children look like assets with an uncertain back-loaded return. To the extent that dynamic complementarities in children's skill formation are quantitatively important, the timing of shocks and parents' ability to vary labor supply can have considerable long-lasting effects on children's outcomes.

Second, we develop a model in which both parents decide whether to work or not; they also face a labor indivisibility constraint, forcing them to choose either part-time or full-time work. An operative participation margin is crucial for a model of female labor supply (Attanasio, Low, and Sánchez-Marcos, 2005; Attanasio et al., 2018), and the assumption of indivisible hours is consistent with the observation that we do not see a continuum of hours-wage bundles in the data (Bick, Blandin, and Rogerson, 2022). Of course, such indivisibilities exacerbate uninsurable wage risk, limiting parents' ability to smooth income shocks. All these features have been found to be important in understanding labor supply decisions (Rogerson, 2024).

Third, we study the mechanisms and use the estimated model to quantify the extent to which general tax-and-transfer policies can mitigate the pass-through of earnings risk to children. In this regard, we advance the view that children's skill formation should be part of the evaluation of the desirability of social insurance policies.

Regarding uninsurable risk and labor supply as a self-insurance mechanism, the most closely related work is Abbott (2022), which investigates the role of incomplete markets for parental investments. The author develops a life-cycle model of a single-parent household that allocates time and monetary resources between consumption and educational investments for a child. The study finds that in the presence of uninsured risk, credit constraints can distort human capital investments in children. Although our study abstracts from credit constraints, we show that the intra-household labor supply choices of two parents is an important channel that affects the extent to which income risk passes through parental investments and children's outcomes.

Finally, the paper relates to Blundell, Pistaferri, and Preston (2008), Blundell, Pistaferri, and Saporta-Eksten (2016), and Carneiro and Ginja (2016) who analyze the impact of realized income shocks on life-cycle consumption and parental investments. A first set of results highlight the key role of family labor supply as a partial insurance mechanism. Moreover, Carneiro and Ginja (2016) find that the pass-through of permanent income shocks to parental investments is small, while they find no evidence to reject the hypothesis of full insurance against temporary shocks. In our work, we use the estimated structural model to address a distinct quantitative question: how does a change in the risk of the parents' wage offer distribution affect children's skills through parental monetary and time investment? The distinction between the impact of a realized shock and a change in risk is perhaps evident in how a given realization of an income shock can have different implications based on the parents' expectations. For example, Carneiro et al. (2021) finds that the realization of the income shocks at different time of the childhood matters for the child's skills level, given a level of permanent household income. This mechanism is also relevant in our context. Furthermore, our model emphasizes the impact of (ex-ante) income risk on child development, which is influenced by parents' expectations regarding the frequency and magnitude of income shocks. Specifically, the effects vary depending on whether parents anticipate experiencing income shocks rarely or frequently, and whether the current shock is small or large compared to expected future shocks.

Also related to our work, Blundell, Pistaferri, and Saporta-Eksten (2018) consider a life-cycle model of a household's time allocation between work, leisure, and child care. Their results suggest that time allocation between children and hours worked interact in the presence of income shocks, as parents' labor supply provides insurance against wage shocks. Our framework extends this previous work in two important directions. First, we model the technology of skill formation, which allows us to study the consequences of income risk on the development of children. Second, the endogenous formation of skills depends on the degree of substitution between parental time and monetary investments in the production of a child's skills, which in turn are affected by the aim to provide insurance to household consumption from income shocks via labor supply responses.

3. Empirical Facts

To address our main questions—how income risk impacts parental decisions in allocating time and money toward children's skill development and how policy can help mitigate such risk—we formulate a quantitative theory of a two-parent household in the following sections. In this theory, the allocation of time between market work and child-related activities, as well as expenditures on children, critically depends on work incentives.

A prerequisite for an empirically plausible theory of parental decisions is demonstrating that actual families respond to changes in work incentives as observed in the data. Additionally, we will consider counterfactual policies that modify the existing tax scheme to partially or fully mitigate the adverse consequences of increased risk faced by families. The effectiveness of these policies depends on whether, and to what extent, the allocation of family resources changes in response to altered tax incentives.

This section presents empirical evidence of parental behavior in response to changes in the tax system's structure. Our focus is on two primary dimensions of parental behavior: expenditures on child-related items and parental time allocation. First, we provide evidence indicating that changes in the tax system, particularly those affecting work incentives, influence parental spending on their children. Then, we present evidence showing that the tax system's structure also affects parental time allocation. These behavioral responses to tax-induced changes in work incentives will operate in the model as mechanisms of partial insurance, helping households cope with changes in wage risk.

We analyze changes in the US tax system, focusing on the variations introduced by Earned Income Tax Credit (EITC) reforms. The EITC stands as one of the largest federal income support programs in the US, providing income transfers contingent on the recipient's employment. Over recent decades, the EITC has undergone several reforms, resulting in changes to recipients' marginal tax rates and work incentives. Appendix A provides an overview of the EITC program and its historical reforms.[1] It is crucial to note that our focus is not on evaluating the efficacy of EITC reforms; rather, we utilize the EITC as a tool to unveil behavioral responses of parents to changes in the tax system.

Parental Expenditures. We investigate parental expenditures through the Consumer Expenditure Survey (CE). The CE is a household-level dataset with detailed information on the expenditures of US households. See Appendix B.2 for more details about the CE data. We consider two types of expenditures: child-related expenditures and expenditures on non-durables. Due to data availability, our focus is on the period from 1996 onward.

Child-related expenditures are categorized into five main groups: clothes, childcare, education, tuition, and toys. Childcare expenditures encompass costs related to babysitting, childcare at home and in other locations, as well as expenses for daycare centers, nurseries, and preschools. Education expenditures cover various items such as school books, supplies, equipment, and other costs, including rentals, test preparation, and tutoring services. Tuition fees cover elementary and high school tuition.

[1] Hotz and Scholz (2003) and Nichols and Rothstein (2016) provide detailed descriptions of the EITC program, its eligibility rules, and the main empirical findings on its effects, including outcomes such as income and labor supply.

Non-durable expenditures include categories such as food, utilities, services, transportation, and personal care, including semidurables like adult clothing. This definition of non-durable expenditures, aligned with the definition proposed by Blundell, Pistaferri, and Preston (2008), excludes spending on housing (furniture, appliances, etc.), vehicles, health, and education. Appendix Table C.1 shows the descriptive statistics for the samples used for the analysis of parental expenditures.

We investigate whether changes in the tax system elicit responses in household child-related expenditures. Our focus is on the reforms of the EITC program. The identification of EITC-induced causal effects is challenging due to the nonrandom nature of eligibility for the program.[2] In our empirical analysis, we address endogeneity concerns by leveraging the quarterly nature of our data and two features of the EITC program. First, one characteristic of the EITC is that tax refunds are typically paid in the second quarter of the year.[3] Second, as discussed in Appendix A, the EITC underwent substantial expansion starting in the early '90s. These two aspects of the program enable us to conduct a difference-in-differences (DiD) analysis by comparing (i) different individual treatment intensities based on the evolution of the program over time; and (ii) expenditures made within the same year-before receiving the tax credit (first quarter) and after the receipt of the tax credit (quarters two to four). A similar empirical strategy is based on the observation that, starting in the second quarter of a year, expenditures might increase due to the receipt of the tax credit.

Our DiD specification is represented by the following equation:

$$Expenditure_{istq} = \alpha_0 + \alpha_1 MaxEITC_{ist} + \alpha_2 MaxEITC_{ist} \times Post_q + X_i'\gamma + \eta_q + \varepsilon_{itq}, \qquad (1)$$

where i represents the household of the interviewee, s is the state of residence, t is the year, and $q \in [1, 2, 3, 4]$ stands for the quarter of the year. Expenditures are expressed in year 2016 real dollars. Following Bastian and Lochner (2022), the variable $MaxEITC$ captures the exposure to the EITC program by measuring the maximum tax credit, in year 2016 real dollars, that a household can receive based on the number of dependent children, the state of residence, and the year.[4] This measure summarizes the size of the EITC program and its evolution over time, while being independent of family income, helping to mitigate previously mentioned endogeneity concerns. $Post$ is an indicator variable with a value of one if the interview is in quarters two to four, and zero for households interviewed in the first quarter. To account for the source of variation in the EITC exposure variable, the vector X includes a full set of interactions

[2]Eligibility criteria and the amount of received benefits depend on several factors such as family composition, family income, and family members' employment status. See Appendix A for more details.

[3]The majority of the program's beneficiaries receive the tax credit in the year following their tax declaration.

[4]The amount of EITC benefits varies with the number of dependent children (one, two, three or more) in the household, hence $MaxEITC$ is indexed by the household subscript i.

Table 1: EITC Exposure and Household Expenditures

	(1) Child Expend.	(2) Child Expend.	(3) Child Expend.	(4) Non-durables	(5) Non-durables	(6) Non-durables
$MaxEITC_{ist} \times Post_q$	0.05***	0.04***	0.05***	0.03	0.02	0.04
	(0.01)	(0.01)	(0.01)	(0.03)	(0.03)	(0.03)
Observations	108,218	108,218	78,038	108,218	108,218	78,038
Mean Dep.Var.	754	754	851	6728	6728	7280
Individual Controls	No	Yes	Yes	No	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes	Yes
Post*Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Post*Num.Children FE	Yes	Yes	Yes	Yes	Yes	Yes
Sample	Whole	Whole	Married	Whole	Whole	Married

Notes: The table shows the effect of changes in the EITC program on household expenditures. Dependent variables: child-related expenditures (columns 1 to 3) and expenditures on other non-durable goods (columns 4 to 6). The variable $MaxEITC_{ist} \times Post_q$ is the interaction of the maximum tax credit, in year 2016 dollars, conditional on state of residence, year, and number of dependent children, and an indicator variable taking the value of 1 if the interview takes place in quarter 2, 3, or 4, and 0 if it takes place in quarter 1. Expenditures are measured quarterly and expressed in year 2016 dollars. Individual controls include respondent's education background (less than high school completion, high school completion, some college, college graduate), marital status, race, gender, and age. Standard errors clustered at the state level are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. See text for further details on the analysis.

between the *Post* indicator and the number of dependent children, state fixed effects, and year fixed effects. In some specifications, we also control for interviewee's characteristics such as education, marital status, race, and age. Additionally, the specification includes fixed effects for quarters of the year to account for seasonal patterns in household expenditures.[5] Finally, ε_{itq} is the error term of the model. Our primary interest lies in the estimation of the coefficient α_2, capturing the effect of exposure to changes in the tax system, specifically in the EITC program, on household child-related and other expenditures.

Table 1 presents the OLS estimates of equation (1) with standard errors clustered at the state level—where policy changes occur. Columns (1) to (3) focus on child-related expenditures, and columns (4) to (6) focus on expenses related to other non-durable goods. Since our model considers two-parent households, the specifications in columns (3) and (6) restrict the sample to married couples. Given the definition of the variable for EITC exposure, all results should be interpreted as intention-to-treat effects (ITT).

[5] The indicator $Post_q$ does not appear in the equation since we control for quarter of the year fixed effects to account for seasonality in expenses.

The analysis in the table suggests that changes in the tax system can affect household expenditures, particularly those associated with child-related expenditures. An increase in EITC generosity leads to a rise in child-related expenditures. In column (1), a \$100 increase in program generosity results in a statistically significant average quarterly increase in child-related expenditures by \$5. This effect is similar for married couples, as shown in column (3). Columns (4) to (6) reveal that the impact on expenditures on non-durable goods is slightly smaller in size and statistically insignificant.

In Table 2, we unpack the effect on child expenditure by examining individual child-related expenses. To maintain consistency with our theoretical model, we focus on the sample of married couples. The analysis considers expenditures on childcare (column 1), clothes (column 2), education (column 3), tuition fees (column 4), and toys (column 5). Some household expenditures appear more responsive to changes in the EITC policy. Specifically, a surge in EITC benefits does not result in significant changes in the average expenditure on childcare or education (excluding tuition fees). Conversely, we observe a positive EITC effect on tuition fees. Additionally, a positive and statistically significant impact of the EITC expansion is detected for expenditures on clothes and toys.

Parental Time Use. We investigate the impact of tax systems on parental time use through the American Time Use Survey (ATUS). See Appendix B.3 for more details about the data. The activities reported in time-use data are aggregated into three main categories: market work, childcare, and residual time. Time spent on market work includes paid work, whether it be a primary job, a secondary job, or other paid activities, conducted either at home or elsewhere. This category encompasses work breaks, additional time at the workplace, traveling to and from work, and job-seeking activities. Time spent on childcare includes the care of infants, general care of older children, medical care of children, playing with children, supervising children or assisting with homework, as well as reading to or talking with children, and other childcare activities.[6] The residual time, referred to as *leisure* time hereafter, is defined as the time in a day not allocated to work or childcare. In essence, leisure time is the complement to the 24-hour day after accounting for time dedicated to work and childcare. This category includes activities such as sleeping, personal care, education, adult care, civic and voluntary activities, religious activities, out-of-home free time and leisure, sports and outdoor activities, in-home free time leisure, as well as media and computing. Appendix Table C.2 shows the descriptive statistics for the samples used for the analysis of parental time use.

We explore the impact of changes in the tax system on parental time use, with a specific focus on the expansion of the EITC program. Similar to our previous analysis, we utilize the

[6] We have also explored with an alternative, slightly different definition of childcare by including travel related to childcare, as proposed by Aguiar, Hurst, and Karabarbounis (2013). The results indicate minimal changes.

Table 2: EITC Exposure and Child-related Expenditures

	(1) Childcare	(2) Child Clothes	(3) Education	(4) Tuition	(5) Toys
$MaxEITC_{ist} \times Post_q$	-0.01	0.02^{***}	0.00	0.03^{***}	0.01^{***}
	(0.01)	(0.00)	(0.00)	(0.01)	(0.00)
Observations	78,038	78,038	78,038	78,038	78,038
Mean Dep.Var.	335	231	42	165	78
Individual Controls	Yes	Yes	Yes	Yes	Yes
Quarter FE	Yes	Yes	Yes	Yes	Yes
Post*Year FE	Yes	Yes	Yes	Yes	Yes
Post*Num.Children FE	Yes	Yes	Yes	Yes	Yes
Sample	Married	Married	Married	Married	Married

Notes: The table shows the effect of changes in the EITC program on child-related expenditures. Dependent variables: childcare expenditures (column 1), expenditures on children's clothes (column 2), expenditures on children's education (column 3), expenditures on tuition (column 4), and expenditures on children's toys (column 5). The variable $MaxEITC_{ist} \times Post_q$ is the interaction of the maximum tax credit, in year 2016 dollars, conditional on state of residence, year, and number of dependent children, and an indicator variable taking the value of 1 if the interview takes place in quarter 2, 3, or 4, and 0 if it takes place in quarter 1. Expenditures are measured quarterly and expressed in year 2016 dollars. Individual controls include respondent's education background (less than high school completion, high school completion, some college, college graduate), marital status, race, gender, and age. Standard errors clustered at the state level are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. See text for further details on the analysis.

measure for maximum EITC benefits. However, due to the yearly nature of time use data and the absence of a longitudinal dimension, we adjust our identification strategy to pinpoint prominent changes in the EITC program and, consequently, in the tax system. We assess the effects of these changes on parental time use by categorizing observations based on their exposure to the EITC program.

We start with the definition of prominent (or relevant) program changes. We consider any change in the maximum available EITC benefits by at least \$200 as prominent. This analysis focuses on the period 1998–2012, and changes are defined based on the schedule at the state-year level for couples with two children.[7] In the second step, we categorize sample units based on their exposure to the EITC program, with eligibility determined by family income. Individuals with a family income below 110 percent of the state-year specific EITC income threshold are considered to have *high* exposure, while the remaining sample units, with income exceeding

[7]Results remain robust to variations, such as using different schedules (e.g., one child) or different definitions for prominent changes. See, for instance, Appendix Table C.3 for the analysis with prominent changes defined as changes by at least \$150.

this threshold by more than 10 percent, are classified as having *low* exposure to the EITC program.[8] In the third step, we compare time usage among individuals interviewed before and after prominent EITC changes to unveil responses to program reforms. This analysis is replicated for families exposed to the program and, as a placebo test, for those families with low exposure to the program due to their likely ineligibility to obtain EITC benefits.[9]

We estimate the following empirical specification:

$$TimeUse_{ist} = \alpha ProgramReform_{st} + \gamma X_i + \mu_s + \rho_t + \varepsilon_{ist}, \tag{2}$$

where $TimeUse_{ist}$ represents the daily minutes spent on a particular activity by parent i residing in state s during year t. The variable $ProgramReform$ is an indicator for a prominent EITC change, defined as a change of at least $200. This indicator is set to zero until the first prominent change in the state s where individual i resides, and become one for all subsequent years. This strategy is inspired by Cengiz et al. (2019) who study the employment impacts of minimum wage changes. The vector X includes control variables for education (categorized as below high school, high school graduates, some college, and college graduates), marital status, age, race, and gender. Additionally, the specification incorporates state (μ_s) and year (ρ_t) fixed effects. The error term of the model is denoted as ε_{ist}. Our focus is on the coefficient α, representing the effect of a change in the EITC schedule on parental time use. The effect is identified through the within-state comparison of individuals before and after a substantial change in program generosity. It is crucial to note that, given the cross-sectional nature of the data, the pre- versus post-prominent change comparison is conducted with different sample units.

Table 3 presents the estimates of (2). We estimate OLS models with standard errors clustered at the state level, where prominent program changes occur. The upper panel displays the analysis for the entire sample. Columns (1) to (3) focus on individuals highly exposed to the EITC program, i.e., those from families reporting an income that does not exceed by more than ten percent the EITC state-year income eligibility threshold. Columns (4) to (6) replicate the analysis for families with low exposure to the EITC program. We conduct the analysis for work time (columns 1 and 4), childcare time (columns 2 and 5), and leisure time (columns 3 and 6).

The analysis in the upper panel of Table 3 highlights two important results. Firstly, for parents highly exposed to the EITC program, prominent program changes induce increases in labor supply. Following a prominent change in EITC benefits, the average parental labor supply increases by about 21 minutes per day. This change represents an increase of more than 12

[8] We choose 110 percent of the EITC income threshold to account for measurement error in family income. The results remain robust to different criteria. Appendix Table C.4 shows results using 100 percent of the EITC income threshold. In this (extreme) case, we assume no measurement error in reported family income.

[9] The cross comparison of the two groups of families—those with high and low exposure to the program—mimics the logic of a DiD estimator.

Table 3: EITC Expansion and Time Use

	(1) Work	(2) Childcare	(3) Leisure	(4) Work	(5) Childcare	(6) Leisure
Program Reform	20.61***	-8.20**	-12.41	1.66	-1.28	-0.37
	(7.62)	(3.91)	(7.78)	(6.54)	(3.14)	(7.28)
Observations	16,829	16,829	16,829	29,472	29,472	29,472
Mean Dep.Var.	167.91	80.11	1191.98	203.8	87.31	1148.88
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Policy Exposure	High	High	High	Low	Low	Low
Sample	Whole	Whole	Whole	Whole	Whole	Whole

	(1) Work	(2) Childcare	(3) Leisure	(4) Work	(5) Childcare	(6) Leisure
Program Reform	24.62*	-11.11*	-13.52	-2.09	-0.38	2.47
	(12.55)	(6.16)	(14.00)	(7.84)	(3.67)	(8.62)
Observations	8,523	8,523	8,523	21,934	21,934	21,934
Mean Dep.Var.	186.35	94.61	1159.04	226.28	107.62	1106.1
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Policy Exposure	High	High	High	Low	Low	Low
Sample	Married	Married	Married	Married	Married	Married

Notes: The table shows the effect of changes in the EITC program on parental time use. Dependent variables: work time (columns 1 and 4), childcare time (columns 2 and 5), and leisure time (columns 3 and 6). Individuals with a family income below 110 percent of the state-year specific EITC income threshold are considered to have high exposure to the program. The upper panel considers the whole sample. The bottom panel restricts the sample to married individuals. The Program Reform is the coefficient for an indicator variable for prominent changes, at least $200 difference in maximum available benefits, in the EITC schedule. The indicator is equal to 0 until the first prominent change in state s where individual i resides, and equal to 1 for all later years. Time use is measured in minutes per day. Individual controls include respondent's education background (less than high school completion, high school completion, some college, college graduate), marital status, race, gender, age and age squared. Standard errors clustered at the state level are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. See text for further details on the analysis.

percent compared to the average of 168 minutes per day worked by parents in our estimation sample. This result aligns with the findings in Agostinelli and Sorrenti (2022), Agostinelli, Borghesan, and Sorrenti (2021), and Bastian and Lochner (2022) concerning maternal labor supply. The rise in time devoted to market work is counterbalanced by a reduction in time dedicated to childcare, which decreases by an average of 8 minutes per day (10 percent of the sample mean). This finding also aligns with the results reported in Bastian and Lochner (2022).[10] The impact on leisure time is smaller compared to the sample mean and statistically insignificant. Secondly, the results appear to support the use of an identification strategy based on exposure to the EITC program. Specifically, none of the effects for families likely unexposed to the EITC (columns 4 to 6) are statistically significant. In other words, we find that families likely unexposed to the program do not respond to changes in the program's generosity.

For consistency with our two-parent household model, the bottom panel of Table 3 replicates the analysis by narrowing the sample to married couples. The main conclusions of the analysis persist despite a reduction in estimates precision, likely attributable to smaller sample sizes.

4. Two-Parent Life-Cycle Model with Children Skill Formation

In this section, we develop the model we later use to quantify how household earnings risk passes through to children's skills. Within a unitary model of a two-parent household, we study the labor supply of both parents, each parent deciding whether to work short or long hours or not working at all, and the allocation of the two parents' time and goods to the formation of the sole children's skills.[11] The household makes such decisions in the face of the idiosyncratic risk that takes the form of shocks to wages and the technology of children's skill formation. The model features a progressive tax-and-transfer system, which allows us to evaluate the effects of several public policies, including means-tested transfers and changes in tax progressivity.

The proposed model abstracts from various mechanisms that could affect household choices and children's skill accumulation. Specifically, we do not model endogenous household saving decisions or the dynamic aspect of wealth accumulation for three main reasons. First, as will become clear in the model section, solving and estimating the model is computationally intensive because it includes four continuous state variables. Adding endogenous saving would

[10] Bastian and Lochner (2022) further delve into a detailed breakdown of the time parents invest in their children, categorizing it into three categories: academic, health, and other investments. Their findings highlight that a significant portion of the time reduction stems from decreased health-related investments in children. Here, we adopt an aggregate measure of time spent with children, viewing it as a proxy for the home environment's quality, thus adopting the view that "quality parenting is a time-intensive process," as discussed by Heckman and Mosso (2014). Furthermore, medical literature has highlighted the importance of maintaining continuity of care throughout childhood to enhance pediatric outcomes (see, for example, Enlow, Passarella, and Lorch, 2017).

[11] See Chiappori and Mazzocco (2017) for a survey article on the unitary model of household behavior. In a recently developed survey conducted for the Innovation Sample of the German Socioeconomic Panel (GSOEP), as reported by Calvo, Lindenlaub, and Uniat (2021), it was found that nearly three-quarters of households equally divide their private consumption between partners. This result aligns seamlessly with our modeling assumption of abstracting from spousal consumption decisions.

introduce another continuous state variable, whose dynamics depend on household saving decisions, thereby adding an additional control variable. Second, empirically, less than fifty percent of U.S. families have positive net worth, with most negative net worth stemming from housing mortgages, which are illiquid assets. Third, our proposed counterfactual policies aim to limit income risk by either increasing tax progressivity or introducing universal basic income. These policies are generally expected to benefit low-income families, who typically lack accumulated wealth and have limited access to credit markets.

4.1. Preferences and Budget Set

The household consists of two parents and a child. We model parental decisions over T periods of the child's life, which we associate with "childhood." The child's age is denoted by t. Each parent is endowed with one unit of time per period that can be allocated to three uses: leisure, hours of work, and time spent with the child.

Preferences. Household's preferences over consumption, c_t, leisure, l_{jt}, of parent $j = \{1, 2\}$, and child's skills θ_t are described by

$$\mathbb{E}_0 \left\{ \sum_{t=0}^{T} \beta^t u\left(c_t, l_{1t}, l_{2t}, \theta_t\right) + \beta^{T+1} v\left(\theta_{T+1}\right) \right\}, \tag{3}$$

where u and v are increasing, concave, and twice continuously differentiable. $\mathbb{E}_0$ indicates the mathematical expectation operator based on available information at childbirth, and β is the time discount factor. Expectations are with respect to the wage offers of both parents, and to the shocks to the technology of skill formation, which we describe later.

Following Del Boca, Flinn, and Wiswall (2014), we allow the parents' valuation of the child's skills over the stage of early childhood, $\{\theta_t\}_{t=0}^{T}$, to differ from that of the terminal value θ_{T+1}. We view θ_{T+1} as the initial condition for the next stage of child development, which we leave unspecified here.

Budget Set. The household's income consists of labor earnings of possibly both parents, net of taxes and transfers, $\mathcal{T}\left(\sum_{j=1}^{2} w_{jt} h_{jt}\right)$, where w_{jt} and h_{jt} denote respectively the wage and the labor supply of parent $j \in \{1, 2\}$, and the function $\mathcal{T}$, whose parameterization we describe later, encompasses all the details of the tax-and-transfer system. To capture the discreteness of hours worked in the data, as documented by Bick, Blandin, and Rogerson (2022), we model the labor supply of each parent as a discrete choice between long-hours, $\overline{h}$, short-hours of work, $\underline{h} < \overline{h}$, and not-working, $h = 0$.

The household's budget constraint is

$$c_t + e_t = \mathcal{T}\left(\sum_{j=1}^{2} w_{jt}h_{jt}\right), \tag{4}$$

where c_t is consumption expenditures and e_t is expenditures related to child's skill formation.[12]

4.2. Technology of Children Skill Formation

Following Cunha, Heckman, and Schennach (2010), we posit a technology of skill formation according to which the child's skills next period θ_{t+1} depend on their current level θ_t, parental time investments, m_{1t}, and m_{2t}, and expenditures on the child, e_t:

$$\theta_{t+1} = \exp\left(z_t\right) f\left(\theta_t, e_t, m_{1t}, m_{2t}\right), \tag{5}$$

where the function f is increasing and concave in each input $(\theta_t, e_t, m_{1t}, m_{2t})$. To capture the inherent risk in the process of skill accumulation, we also assume that the process of child development is hit by stochastic shocks that disturb the return to parental investment for a given child's skill level, akin to random shifts in the production possibility frontier in standard production theory. Such technology shocks follow an AR(1) process:

$$z_{t+1} = \mu_z\left(1-\rho_z\right) + \rho_z z_t + \sigma_\eta \eta_{t+1}, \quad \text{with} \quad \eta_{t+1} \overset{iid}{\sim} \mathcal{N}\left(0,1\right), \tag{6}$$

where μ_z is the unconditional mean of the shocks, ρ_z governs the persistence of such shocks, and σ_η is the standard deviation of independent and identically distributed (i.i.d.) normal innovations, η_t. The initial level of the child's skills θ_0 is random and drawn from a distribution that allows θ_0 to be correlated with the wage offers of both parents, in a parametric way that we describe in the estimation section.

4.3. Wage Processes

As we consider labor supply decisions along the extensive margin, in the model, there is a distinction between the distribution of offered wages, a latent object, that we take as exogenous, and the distribution of accepted wages, which we can instead read from the data and contrast with that implied by the model.

More specifically, in the model, each parent has three available options at hand: not-working,

[12] Consistent with the U.S. tax system, in (4) we model joint taxation of parents' earnings. Bronson and Mazzocco (2023) study the implications of individual versus joint tax systems for household decisions.

working short-hours, and working long-hours. Intuitively, whether a parent works or not and whether he or she works short- or long-hours depends on the labor supply decision of the other parent. In fact, for each parent, there are four reservations wages that fully describe his or her labor supply. To see this more clearly, think of a one-parent family. In that setup, the labor supply decision of the single parent is described by two reservation wages; one defined as the value of the wage that makes the parent indifferent between working short-hours and not-working, another that makes the parent indifferent between working short-hours and working long-hours. Now, in the case of a two-parent family, things change as one parent's indifference among alternative labor supply choices generally depends on whether the other parent is working, and if so, how many hours he or she is working. This interdependence comes from sharing resources within the family, which generates income effects that operate through changes in each parent's consumption.

Concretely, we assume that the log of the wage offered to parent $j \in \{1, 2\}$ at time t is

$$\log w_{jt} = a_j + b_j t + \varepsilon_{jt}, \tag{7}$$

where b_j is the growth rate of the wage, which when we turn to estimation we allow to vary by the parent's gender, and ε_{jt} is an innovation that we assume to follow an AR(1) process:

$$\varepsilon_{jt} = \rho_j \varepsilon_{jt-1} + \sigma_{\nu j} \nu_{jt}, \quad \text{with} \quad \nu_{jt} \overset{iid}{\sim} \mathcal{N}(0, 1), \tag{8}$$

where the persistence parameters ρ_j and standard deviations $\sigma_{\nu j}$ are again allowed to vary by the parent's gender. The initial wage offers $\{w_{10}, w_{20}\}$ are random and drawn from a joint Normal distribution that allows for the offers of both parents to be correlated.[13]

Finally, note that conditional on working, the wages of possibly both parents fluctuate over the life-cycle, subject to stochastic shocks. This is consistent with the large and growing evidence that US households face substantial idiosyncratic earning risk (see, e.g., Blundell, Pistaferri, and Preston, 2008; Blundell, Pistaferri, and Saporta-Eksten, 2016, 2018; Heathcote, Storesletten, and Violante, 2014). More specifically, wages grow over time at a constant rate, which is allowed to differ by parent's gender, and are hit by transitory but persistent shocks around their trend. Given the life-cycle nature of the model, such transitory shocks can have nontrivial permanent effects insofar as they occur sufficiently close to T. The extent of such permanent effects depends on the magnitude and persistence of wage shocks, empirical objects

[13] De Nardi, Fella, and Paz-Pardo (2020) provide advancements in the estimation of flexible wage processes. In particular, the authors estimate a stochastic wage model where wage shocks are age-dependent, and wage risk depends on the worker's rank in the wage distribution. While the authors observe a long panel for their workers, specifically individuals aged 25 to 60, our short panel of parents ranges from when their children are 5-6 years old to 11-12 years old. Such data limitation restricts our ability in estimating a more flexible wage process.

that we estimate from the data.

4.4. Household's Problem

We now study the household's problem and its implications for the child's skills. The child's skills in the next period depend on parental time allocations and expenditures in the current period, making the problem dynamic.

Given the exogenous wage processes described by (7)-(8), the initial wage offers $\{w_{j0}\}_{j=1}^{2}$ for both parents and the initial level of the child's skills θ_0, the household's maximization problem is given by:

$$\max_{\left\{c_t, e_t, \{h_{jt}, l_{jt}, m_{jt}\}_{j=1,2}\right\}_{t=0}^{T}} \mathbb{E}_0 \left\{ \sum_{t=0}^{T} \beta^t u\left(c_t, l_{1t}, l_{2t}, \theta_t\right) + \beta^{T+1} v(\theta_{T+1}) \right\}, \tag{9}$$

subject to

$$l_{jt} + h_{jt} + m_{jt} = 1, \tag{10}$$

$$c_t + e_t = \mathcal{T}\left(\sum_{j=1}^{2} w_{jt} h_{jt} \right), \tag{11}$$

$$\theta_{t+1} = \exp\left(z_t\right) f\left(\theta_t, e_t, m_{1t}, m_{2t}\right). \tag{12}$$

To cast the household's problem in recursive form, we let $\mathbf{s} \equiv \{\log w_1, \log w_2, z\}$ denote the vector of exogenous state variables, that includes log wages for each parent and log TFP of the child's skill formation technology. The endogenous state variable is the current level of child's skills θ.

The value function for $t \leq T$ thus satisfies the following Bellman equation:

$$V_t\left(\theta, \mathbf{s}\right) = \max_{c_t, e_t, \{h_{jt}, l_{jt}, m_{jt}\}_{j=1,2}} \left\{ u\left(c, l_1, l_2, \theta\right) + \beta \mathbb{E}_{\mathbf{s}'|\mathbf{s}} V_{t+1}\left(\theta', \mathbf{s}'\right) \right\}, \tag{13}$$

subject to the constraints (10)-(12). The expectation is taken with respect to both parents' wage offer shocks, as well as the child development shock.

5. Bringing the Model to the Data

In this section, we describe the model's parameterization. We begin by laying out the parametric assumptions about preferences, technology, and the tax-and-transfer system. We then describe how we pin down parameter values. Finally, we discuss the model's goodness of fit.

5.1. Functional Forms

Preferences. We assume the following functional form for the household's utility function:

$$u\left(c,\theta,l_1,l_2\right)=\frac{c^{1-\gamma_c}}{1-\gamma_c}+\alpha_\theta\frac{\theta^{1-\gamma_\theta}}{1-\gamma_\theta}+\alpha_{l_1}\frac{l_1^{1-\gamma_{l_1}}}{1-\gamma_{l_1}}+\alpha_{l_2}\frac{l_2^{1-\gamma_{l_2}}}{1-\gamma_{l_2}}. \tag{14}$$

The triplet $(\alpha_\theta,\alpha_{l_1},\alpha_{l_2})$ governs the relative weight of children's skills and parents' leisure in household's utility, respectively. The parameters $(\gamma_c,\gamma_\theta,\gamma_{l_1},$ and $\gamma_{l_2})$ pin down the elasticities of the marginal utilities of consumption, child's skills, and parents' leisure with respect to c, θ, l_1, and l_2, respectively.

Technology. The technology of skill accumulation is a multi-layer nested constant-elasticity-of-substitution (CES) production function, which allows for various degrees of substitution between child-related expenditures, parental time, and dynamic complementarity in child development:

$$\theta'=\exp\left(z\right)f; \tag{15}$$

$$f=\left(\omega_f\theta^{\frac{\sigma_f-1}{\sigma_f}}+\left(1-\omega_f\right)I^{\frac{\sigma_f-1}{\sigma_f}}\right)^{\frac{\sigma_f}{\sigma_f-1}}; \tag{16}$$

$$I=\left(\omega_I e^{\frac{\sigma_I-1}{\sigma_I}}+\left(1-\omega_I\right)M^{\frac{\sigma_I-1}{\sigma_I}}\right)^{\frac{\sigma_I}{\sigma_I-1}}; \tag{17}$$

$$M=\left(\omega_M m_1^{\frac{\sigma_M-1}{\sigma_M}}+\left(1-\omega_M\right)m_2^{\frac{\sigma_M-1}{\sigma_M}}\right)^{\frac{\sigma_M}{\sigma_M-1}}. \tag{18}$$

The function f captures how current skills, θ, and a composite of "household investment," I—a CES aggregate of child-related expenditures, e, and parental time, M—contribute to child's skill formation. Note that we allow for a flexible degree of substitutatibility between the two parental time inputs. For each of the three CES aggregators, the parameter σ determines the elasticity of substitution between inputs, while the parameter ω governs input shares. As mentioned in Section 4.2, the process of skill development is assumed to be stochastic and subject to persistent shocks, z_t.

Taxes and Transfers. The US tax-and-transfer system is rather complex, involving a mix of means-tested transfers and progressive income taxation with multiple tax brackets and tax deductions and credits. To parsimoniously capture such complexity, the literature typically adopts a simple, yet empirically plausible tax function, which can be readily estimated using

TAXSIM data. Specifically, we assume that after-tax household's income is

$$\mathcal{T}(Y) = \chi_1 (\chi_3 + Y)^{1-\chi_2}, \tag{19}$$

where Y is total household earnings, the sum of the two parents' earnings, χ_1 measures the overall level of taxation, χ_2 measures tax progressivity, and χ_3 is the unconditional minimum income available in the case of zero earnings. When $\chi_1 = 1$ and $\chi_2 = \chi_3 = 0$, income is not taxed. On the other hand, when $\chi_2 = \chi_3 = 0$, taxes are proportional to income, $\mathcal{T}(Y) = \chi_1 Y$. Finally, when $\chi_2 > 0$ the tax system is progressive.

Child Skills' Terminal Value. In the model, parents make decisions over four periods ($T = 4$), while child development unfolds over five periods ($T + 1$). Each period corresponds to two calendar years. The first model period coincides with when a child is 5-6 years old and the last with when the child is 13-14 ($T + 1$). This choice is driven by the structure of the main data we use for estimating the model (National Longitudinal Study of Youth 1979), which features waves of data collections every other year.[14]

Finally, we close the model by specifying a final period terminal value for the dynamic problem. This continuation value aims to capture the stream of future utility household receive as a function of a child's end-of-childhood skills. This function captures the altruistic preference of household for their children's adult life. This specification follows a similar approach in Del Boca, Flinn, and Wiswall (2014) and is computationally attractive because it avoids solving for the entire children's future life-cycle as a function of their inherited skills.[15] Specifically, we assume

$$V_{T+1}(\theta) = \tilde{\alpha}_\theta \frac{\theta^{1-\tilde{\gamma}_\theta}}{1-\tilde{\gamma}_\theta}, \tag{20}$$

and allow the parameters $(\tilde{\alpha}_\theta, \tilde{\gamma}_\theta)$ to differ from the preference parameters specified for all the previous periods.

5.2. Additional Data for the Model Estimation

For the estimation of the model, we also take advantage of the National Longitudinal Study of Youth 1979 (NLSY79), and their Children survey (NSLY79-C). Our sample represents the subsample of mothers of the original representative sample of youth in 1979. Individuals in this

[14]Interviews were conducted annually before 1994, but children's information were collected only every other year starting from 1986. From 1994 onward, both adults and children data collections occurred biannually.

[15]A similar approach has been used in different context by De Nardi (2004), who model the parents' utility of bequeathing their financial assets to their children.

data are followed over time, and their children are surveyed every two years starting from 1986. Data include labor market information for mothers and their spouses, such as employment status, hours worked and earnings. The accepted hourly wages for both parents were constructed by dividing annual earnings per annual hours worked.

The data set includes relevant information about test scores of children during childhood. We use as our measure of skills the available scores in the Peabody Individual Achievement Test (PIAT) in mathematics and reading. To construct the index of child development, we take the average of the three PIAT raw scores available (Math, Reading-Comprehension and Reading-Recognition) for every child, and divide it by the total maximum points available in PIAT (84). The constructed index varies between 0 (no correct answer) and 1 (the child scored a perfect score in all of the three tests).

5.3. Estimation Procedure

Our estimation algorithm consists of two steps. In the first step, we set/estimate certain model's parameters directly outside the model. This allows us to reduce the computation burden of the estimation of the full model. In the second step, we estimate the rest of the model's parameters via the Simulated Method of Moments (SMM) estimator. The technology of skill formation is estimated in the second step, allowing us to combine information about test scores, time allocations, and monetary investments from three disjointed datasets. Due to this feature of the data, estimating the technology outside the model is not feasible. However, simulation-based estimation enables us to overcome this limitation.

5.3.1. First Step

We exogenously set the value of the discount factor β. Additionally, outside the model, we estimate a subset of parameters, including (ii) the triplet of the tax-and-transfer system, represented by χ_1, χ_2, and χ_3; and (iii) the initial distribution of skills at age 5. A concise summary of our approach is as follows:

- The annual discount factor is set to be 0.96, which implies a one model's period (two calendar years) β of 0.9216 ($\beta = 0.96^2 = 0.9216$).

- The tax-and-transfer system $\mathcal{T}(Y)$ is approximated based on TAXSIM data. TAXSIM is the NBER program that calculates individual-level tax liabilities based on simulating the actual US tax-and-transfer system. We focus on the tax system as it is in 1996. We adopt a nonlinear least-squares procedure to estimate the tax function in (19). Note that in the model, a period is two years, so Y denotes two-year household labor income, and

$\mathcal{T}(Y)$ is its after-tax counterpart. The obtained tax parameters are: $\chi_1 = 3.41$, $\chi_2 = 0.118$, $\chi_3 = 2391$. Appendix Figure C.1 shows the goodness of fit.

- The initial distribution of skills at age 5 (the first period of our model) is estimated directly taken from NLSY data. In particular, the initial heterogeneity of skill endowment among 5- to 6-year-old is parameterized by a normal distribution $\theta_5 \sim N(\mu_{\theta,5}, \sigma^2_{\theta,5})$, and the mean and variance is estimated directly in the data. We find that the initial distribution of skills has a mean of 0.1893 and a standard deviation of 0.0586.

5.3.2. Second Step

We estimate the rest of the 29 parameters "internally" by the simulated method of moments (SMM). The parameters that we aim to estimate are:

- Flow utility $u(c, l_1, l_2, \theta)$: $\gamma_c, \alpha_\theta, \gamma_\theta, \alpha_{l_1}, \gamma_{l_1}, \alpha_{l_2}, \gamma_{l_2}$.
- Terminal condition $V_{T+1}(\theta)$: $\tilde{\alpha}_\theta, \tilde{\gamma}_\theta$.
- Production function $f(\theta, e, m_1, m_2)$: $\omega_f, \omega_I, \omega_M, \sigma_f, \sigma_I, \sigma_M$.
- TFP process: $\mu_z, \rho_z, \sigma^2_\eta$.
- Wage process: $\left\{a_j, b_j, \rho_j, \sigma^2_{\nu j}\right\}_{j=1}^{2}$.
- Initial joint distribution of wages and skill: $\rho_{w_1,w_2}, \rho_{w_1,\theta}, \rho_{w_2,\theta}$.

We estimate wage processes' parameters and initial joint wages and skill distribution inside the model to account for the fact that we observe wage offers solely for individuals who accepted them. In related work, which also includes the extensive margin of labor supply, Blundell, Pistaferri, and Saporta-Eksten (2018) estimate the wage equations outside the model, correcting for sample selection via Heckman correction method (Heckman, 1979). Our estimation method is internally valid concerning the selection of observed wages induced by the extensive margin of labor supply for both parents.

5.3.3. Simulated Method of Moments

The simulated method of moments requires solving and simulating the model to construct the model's counterpart of the empirical moments we observe in the data.

Algorithm 1. *The estimation algorithm, which starts with an initial n=0 guess for the above 29 parameters (Ω^0), follows the following steps:*

- ***Step 1.*** *Given the current n-th guess of the vector of parameters* (Ω^n)*, we solve via backward induction for the policy functions for all the endogenous choices*

$$\{c_t(\cdot\,;\Omega^n), e_t(\cdot\,;\Omega^n), m_{1t}(\cdot\,;\Omega^n), m_{2t}(\cdot\,;\Omega^n), l_{1t}(\cdot\,;\Omega^n), l_{2t}(\cdot\,;\Omega^n), h_{1t}(\cdot\,;\Omega^n), h_{2t}(\cdot\,;\Omega^n)\}_{t=0}^{T}.$$

- ***Step 2.*** *We simulate the joint distribution of exogenous state variables in the population:*

$$\{\theta_{i,0}, \{w_{i1t}, w_{i2t}, z_{it}\}_t\}_i \ ,$$

which includes the realization of the initial heterogeneity in the first period skill endowments,the distribution of life-cycle wage paths for each household, as well as the distribution of life-cycle TFP paths for each household.

- ***Step 3.*** *Given the simulated distribution of exogenous state variables, we use the policy functions from Step 2 to generate the distribution of the endogenous choices and outcomes:*
  - *Life-cycle path of children's skills:* $\left\{\{\theta_{it}\}_{t=1}^{T+1}\right\}_i$.
  - *Labor supply:* $\{h_{1t}, h_{2t}\}_{t=0}^{T}$.
  - *Leisure:* $\{l_{1t}, l_{2t}\}_{t=0}^{T}$.
  - *Time spent with child:* $\{m_{1t}, m_{2t}\}_{t=0}^{T}$.
  - *Consumption and child-related expenditures:* $\{c_t, e_t\}_{t=0}^{T}$.

- ***Step 4.*** *We use the simulated distributions from Step 3 to construct the simulated counterparts* (M^{Sim}) *of the empirical moments estimated in the data* (M^{Data})*. This allows us to construct the SMM objective function, and to update the guess of parameters:*

$$\Omega^{n+1} = \arg\min_{\Omega}(M^{data} - M^{Sim}(\Omega))'(M^{data} - M^{Sim}(\Omega)).$$

- ***Step 5.*** *We set* $n = n+1$ *and repeat Step 1 until the parameters converge* $(\Omega^n = \Omega^{n+1})$.

Set of Moments. We select several informative moments by combining multiple data sources. Although the estimator uses all the information from the moments jointly, which does not allow to link a particular moment to the identification of a particular parameter, we provide the intuition behind the value for identification of each set of moments. The first set of moments are calculated from the NLSY79-C data:

- A set of ten moments about the life-cycle profile of mean and standard deviation of skills, which will be informative about the production of skills and child development (Panel A of Figure 1).

- A set of thirty-two moments describing the life-cycle profile of maternal and paternal hours worked, accepted wages, as well as the part-time and full-time employment rates for both mothers and fathers. This information will help us to understand the consumption-leisure-parenting trade-off, as well as the wage offer functions (Panels B-D of Figure 1).

- A set of five moments, that include the correlation between a child's skills and both spouses' accepted wages and earnings. This set of moments is informative about the joint distribution of spouses' wage offers and the skills of a child. Moreover, the moments include the correlation of accepted wages between spouses (Table 5).

- A set of ten moments characterizing the distribution of spouses' joint labor supply decisions. These moments are informative about the relative importance of leisure in the household utility, the relative importance of parental time in the production function, as well as the complementary of maternal and paternal time investments in the production of skills (Figure 2).

- A set of two moments from ATUS and CE data which define the relative expenditure and time investments between mothers working full-time and other mothers. This information is informative about the complementarity between monetary and time investments in skill production, as well as on the substitution between hours worked and parental investments in a child's skills.

In total, we have 58 moments used to identify 29 parameters. The model's estimates and sample fit of all moments are reported in the following subsection.

5.4. Parameter Estimates and Model Fit

Table 4 summarizes parameters' estimates. Next, instead of discussing each parameter value in isolation, we quantify the implications of the estimated parameters for the model's ability to reproduce many data moments. For example, in our model, the intra-household allocation of the time spent with the child and child-related expenditures are critical determinants of children's skill accumulation. Hence, getting a good model fit of the parents' wage acceptance decisions, joint labor supply, and their relationship with children's skills is paramount for quantifying the income risk pass-through and policy valuation.

To begin, Table 5 shows that the model does reasonably well in generating the observed correlations between child skills and parents' hourly wages (w_1, w_2) and earnings (y_1, y_2), and the correlation between the hourly wages of the two parents. These correlations are unconditional; we calculate them as an average over childhood (children 5-14 years old). However, extensive

Table 4: Parameter Estimates

Symbol	Point Estimate	Standard Error	Symbol	Point Estimate	Standard Error
A. Preferences					
γ_c	2.5462	0.0232			
γ_θ	0.2267	0.0579	α_θ	4.7032	0.4113
γ_{l_1}	5.7242	0.0379	α_{l_1}	49.8411	2.6372
γ_{l_2}	5.7680	0.0575	α_{l_2}	64.1651	5.3799
$\tilde{\gamma}_\theta$	2.4733	0.6928	$\tilde{\alpha}_\theta$	18.3934	4.8688
B. Technology					
ω_f	0.9069	0.0031	σ_f	0.9902	0.0189
ω_I	0.1445	0.0054	σ_I	2.9109	0.1426
ω_M	0.5830	0.0175	σ_M	0.5883	0.0884
μ_z	0.4206	0.0087	ρ_z	0.4312	0.0195
σ_η	0.2255	0.0063			
C. Wage Process					
a_1	2.9400	0.0211	b_1	0.0576	0.0057
ρ_1	0.5345	0.0369	$\sigma_{\nu 1}$	0.6700	0.0371
a_2	1.7301	0.0337	b_2	0.1359	0.0063
ρ_2	0.6159	0.0294	$\sigma_{\nu 2}$	0.8744	0.0530
$\rho_{w_1,\theta}$	0.4508	0.0556	$\rho_{w_2,\theta}$	0.1931	0.0380
ρ_{w_1,w_2}	0.0519	0.0151			

Notes: This table reports the model's parameter estimates. Parameters are estimated by the simulated method of moments (SMM). The Standard errors are calculated based on the asymptotic variance formula for the SMM estimator. Further details on the computation of the standard errors can be found in Appendix D.

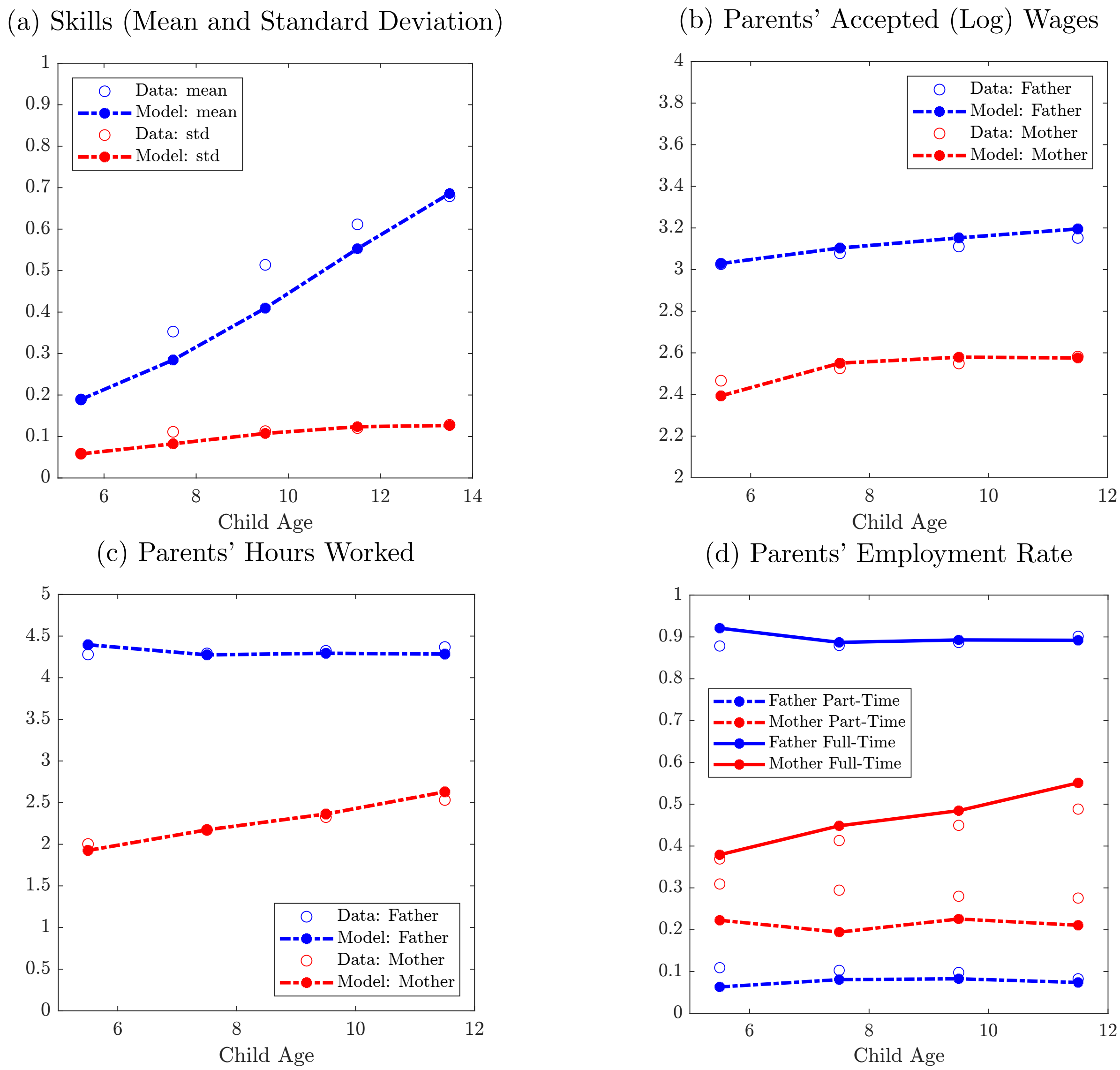
Table 5: Correlation Between Parent Wages and Child Skills

Moment	Data	Model
corr (θ, w_1)	0.1721	0.1845
corr (θ, w_2)	0.1080	0.0875
corr (θ, y_1)	0.1556	0.1719
corr (θ, y_2)	0.1324	0.1210
corr (w_1, w_2)	0.2962	0.3552

Notes: This table shows the in-sample fit of the estimated model. The five moments represent the correlations between children's skill levels and accepted wages and earnings of both parents, and the correlation between the accepted wages of the parents.

literature finds that the children's skill development process critically depends on the early stages of childhood, suggesting that the timing of parental investments matters. Figure 1 shows the model successfully replicates the skill profiles in terms of means and standard deviations, parents' accepted wages, hours worked, and employment rates *conditional* on child age.

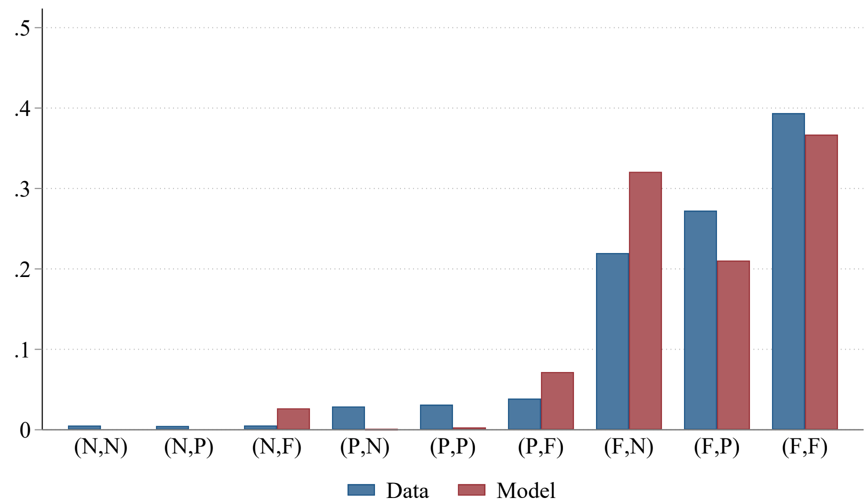
Figure 1: Goodness of Fit: Life-Cycle Profiles



Notes: Panel (a) shows the in-sample fit of the estimated model with respect to the life-cycle profile of means and standard deviations of children's skills. Panels (b)-(d) show the in-sample fit with respect to the moments describing the life-cycle profile of maternal and paternal accepted wages, biannual hours worked (thousands), as well as the part-time and full-time employment rates, respectively.

Figure 2 shows the in-sample fit of the distribution of joint household labor supply decision. The nine different pairs represent the combinations of non-working, part-time, and full time working among parents. The blue bars represent the empirical shares of families for each possible case. The red bars represent the predicted model's counterpart. Overall, the model replicates fairly well the observed joint labor supply decisions among parents: fathers are more likely to work full time, and the mode of the sample is that both parents work. When father does not work full time, the mode is that mothers work full time. These facts are replicated by the estimated model.

Figure 2: Distribution (Frequency) of Joint Labor Supply



Notes: The figure shows the in-sample fit of the estimated model with respect to the distribution of spouses' joint labor supply. The nine different pairs represent the nine possible combinations of labor supply decisions (non-working, part-time and full-time) between parents. The first element of the pairs is for fathers, while the second element represents the mothers' labor supply decision.

6. Quantifying the Pass-Through of Parental Income Risk

In this section, we implement several experiments aimed at quantifying the mechanisms and the extent to which parental wage risk passes through to children's skill development.

6.1. Wage Risk Shocks and Child Development

We begin by looking at how a *mean-preserving spread* of the parents' wage offer distributions affect child development. We perform three exercises: (1) we vary the standard deviation of father's wage shock from 0.5 to 1.5 its estimated level, while keeping everything else fixed; (2) we vary the standard deviation of mother's wage shock from 0.5 to 1.5 its estimated level; (3) we vary the standard deviation of both the father and mother's wage shock from 0.5 to 1.5 their estimated level. The outcome variable of interest is the skill of the child at the final stage. Figure 3 shows the results.

Implementation Details. To implement a mean-preserving spread, we keep the mean wage offer at baseline level. Recall that we have assumed the wage offer process is

$$\log w_{jt} = a_j + b_j t + \varepsilon_{jt},$$

with

$$\varepsilon_{jt} = \rho_j \varepsilon_{jt-1} + \sigma_{vj} v_{jt}.$$

So the distribution of log wage offer (conditional on t) is

$$\log w_j \sim \mathcal{N}(a_j + b_j t, \sigma_{\varepsilon j}),$$

where

$$\sigma_{\varepsilon j}^2 = \frac{\sigma_{vj}^2}{1-\rho_j^2}.$$

Since w_j exhibits a log-normal distribution, the mean of w_j is

$$\exp\left(a_j + b_j t + \frac{1}{2}\sigma_{\varepsilon j}^2\right) = \exp\left(a_j + b_j t + \frac{1}{2}\frac{\sigma_{vj}^2}{1-\rho_j^2}\right).$$

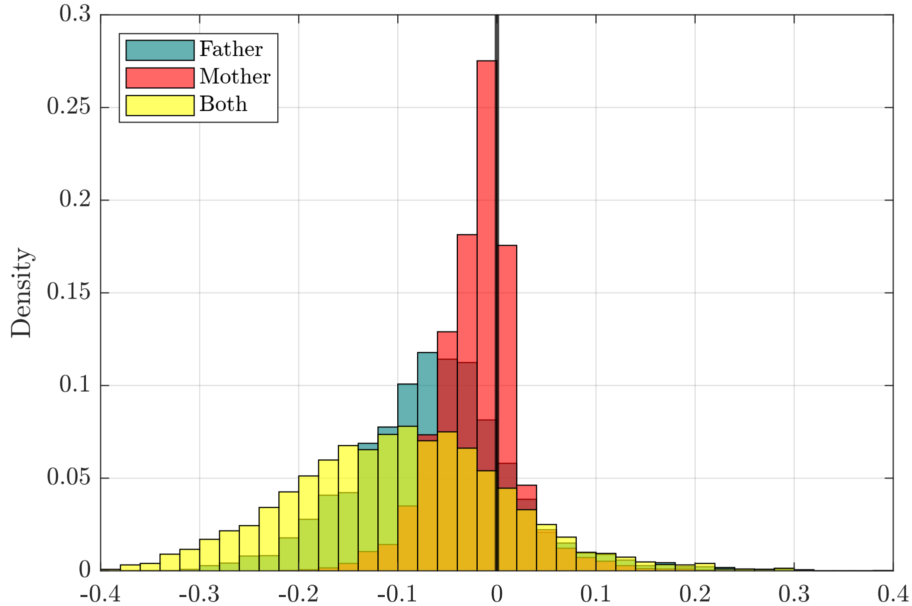
In all cases, then, we adjust the mean by $\frac{\sigma_{vj}^2(baseline) - \sigma_{vj}^2(experiment)}{2(1-\rho_j^2)}$ when we change σ_{vj}.

Further, to generate the initial correlation between wages and skills, we have assumed that the initial skill is drawn from a joint distribution that also depends on wage offers. In the exercises here, we are only changing the standard deviation of wage shocks, but the correlation of initial skill and wage offers are kept fixed. As a result, this exercise effectively also changes the distribution of initial skills.

Discussion. Figure 3 plots the distribution of skill changes, measured as a ratio of the standard deviation of skills in the baseline, to a larger (50% more compared to the baseline) father wage offer shock (blue), mother wage offer shock (red), and both (yellow). In all cases we increase the standard deviation of the wage *offer* distributions, as opposed to the distribution of accepted wage offers, while we keep the mean wage offers fixed at their baseline level. Whether the standard deviations of the accepted wage distributions rise, fall, or stay the same as in the baseline, depends on parents' labor supply choices, partly reflecting a higher option value of working.

Three main results stand out. First, in all three cases wage risk is detrimental for children's skill accumulation. The impact on children's skills is consistently negative, with the distribution of effects displaying an average decline, signifying a reduction in the overall average skill level.

Figure 3: Distributions of Skill Changes to a Mean-Preserving Spread in the Wage Offer Shocks



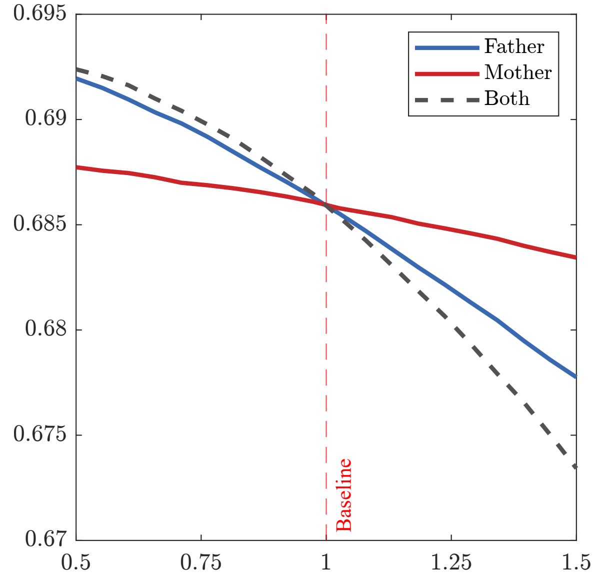
Notes: This figure plots the distribution of skill changes, measured as a ratio of the standard deviation of skills in the baseline, to a larger (50% more compared to the baseline) father wage offer shock (blue), mother wage offer shock (red), and both (yellow).

Second, when comparing the impact of wage offer risk between fathers and mothers, our results show that the increased risk associated with fathers has a more substantial negative effect on skill levels. Furthermore, the father's wage risk introduces higher heterogeneity in the skill effects, with a range spanning from -0.3 to +0.2 standard deviations, in contrast to the wage offer risk of mothers. Consequently, when fathers experience risk shocks, mean skill levels decline, and the effects are distributed with greater inequality among children compared to when mothers undergo the same shocks. Third, in cases where the shock affects both parents, a noticeable decline in average skill levels is observed, accompanied by highly heterogeneous impacts among children. This suggests a significant impact on both the overall skill level and the distribution of skill effects when both parents are exposed to higher wage risk.

Figure 4 shows the impact of increasing and decreasing wage offer risk on the mean skill levels relative to the baseline by different shock sizes. Children's mean skill levels are substantially more sensitive to changes in the wage offer risk of the father than that of the mother. Perhaps not surprisingly, the negative effect of increased risk on skills is the largest when we hit the wage offer process of both parents. Importantly, the combined effect is larger than the sum of mother and father.

Figure 5 zooms in on the transmission mechanisms. We begin by discussing the implications for income and expenditures; see figures in panel (a). In all cases, after-tax income falls as we increase the wage offer risk of the parents. Such a fall in disposable income is associated with a

Figure 4: The Mean Effect of Wage Shock Dispersion



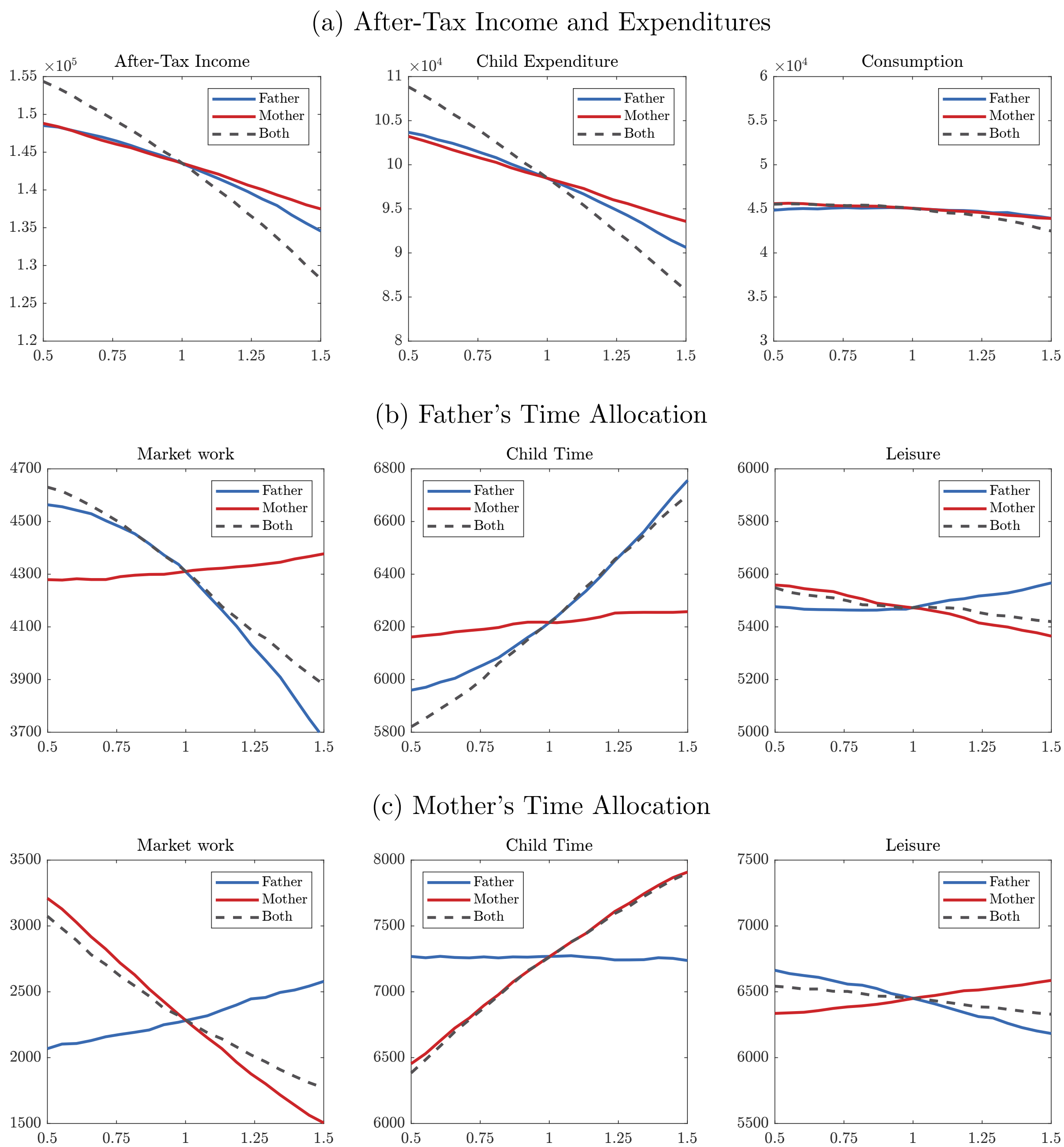
Notes: This figure plots the mean skill levels on the y-axis (last period) and the change in the standard deviation of the wage offer distribution on the x-axis, relative to the baseline. The standard deviation of skills in the last period is 0.13. Consequently, the change from 0.5 to 1.5 in the standard deviation of the wage offer distribution for fathers (blue line) induces a change in the mean skill levels from 0.692 to 0.678, which represents a change of approximately 15% of a standard deviation of final skills.

sizable reduction in expenditures on children, whereas parental consumption remains virtually unchanged. Parents facing increased wage risk respond by smoothing their own consumption at the expense of child-related expenditures. To partly offset this reduction in child-related expenditures, parents increase child time; see figures in panels (b) and (c).

6.2. Can the Social Safety Net Mitigate Children Skill Losses?

We now evaluate how progressive taxes and Universal Basic Income (UBI) can mitigate the adverse effect of income risk on children's skill accumulation. We begin with an experiment involving an increase in the tax system's progressivity, then turn to Andrew Yang's UBI proposal, which consists of a $1,000 per month lump-sum transfer to every American adult over 18. Both policies, while different, can reduce the extent to which income risk passes through the process of child development. On the one hand, increasing tax progressivity represents an insurance mechanism that disproportionally taxes individuals in good times and less so in bad times. On the other hand, UBI provides insurance in terms of the minimum disposable family income, unconditionally to the realized state of the world in terms of income risk. In particular, UBI guarantees a floor for the after-tax labor income of families.

Figure 5: Inspecting the Transmission Mechanisms of Increased Wage Risk



Notes: This figure shows the variable of interest on the y-axis and the size of the change in the standard deviation of the wage offer distributions on the x-axis.

6.2.1. Toward a More Progressive Tax System

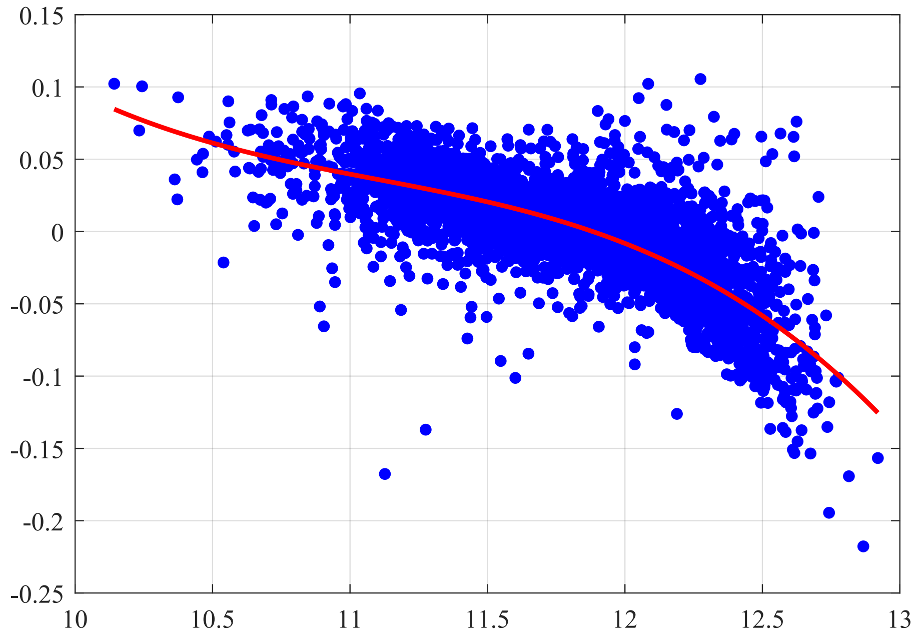
Let us think of the following thought experiment. Overnight the government changes the progressivity of the tax-and-transfer system toward more progressive taxes. Is the magnitude of the wage risk pass-through on children's skill levels larger or smaller relative to the current, less progressive system in place? To answer this question, we capitalize on the simple tax function in (19), which parsimoniously describes the complex US system of taxes and transfers with three parameters (χ_1, χ_2, and χ_3).

We are interested in comparing two tax systems that differ in terms of progressivity but have the same overall tax rate level. To implement this exercise, we proceed as follows. We increase the progressivity parameter χ_2 from its benchmark level 0.118, to twice its level, 0.236, while readjusting the level parameter χ_1 so that the effective tax rate for the median household is unchanged. In the baseline economy, the median household (in terms of the average annual income) has an effective tax rate of 16.2%. Appendix Figure C.2 shows the relationship between pre- and post-tax/transfer income in the baseline (solid line) and after increasing tax progressivity (dashed line). As apparent from the figure, moving toward a more progressive tax-and-transfer system tilts the pre- and post-tax income relationship by giving more post-tax income at the lower end of the pre-tax income distribution and less at the higher end of the pre-tax income distribution.

To begin, we study how the tax progressivity change impacts children's skill levels. Figure 6 shows children's final skill changes compared to the baseline after the increase in tax progressivity. Each dot represents a simulated household. The x-axis plots the log average annual post-tax income at the household level, and the y-axis plots the change in the child final skill in unit of the skills' standard deviation in the baseline. First, the change in progressivity has heterogeneous effect on skills: a negative effect on skills for high-income, a positive one for low-income. Second, quantitatively, at the lower end of the income distribution the positive effect ranges between 5 and 10 percent of the standard deviation of children's skills in baseline. At the higher end of the income distribution, the negative effect is sizable, ranging from 10 to 20 percent of the skills' standard deviation.

Figure 7b shows the distribution of skill changes for a 50% increase in the standard deviation of the wage offer shock for mother, father, and both, under a more progressive tax system. Figure 7a reproduces the results in Figure 3 to ease comparison. Overall, enhanced tax progressivity mitigates the transmission of increased wage risk across the board through the standard insurance effect of progressive taxation. The distributions all shift to the left, implying skill losses on average, but by a lesser amount than in the baseline, less progressive tax-and-transfer system. Moreover, increased progressivity attenuates the unequal impact of increased wage risk on children's skill, as the effect distributions are visibly more concentrated compared to the baseline scenario.

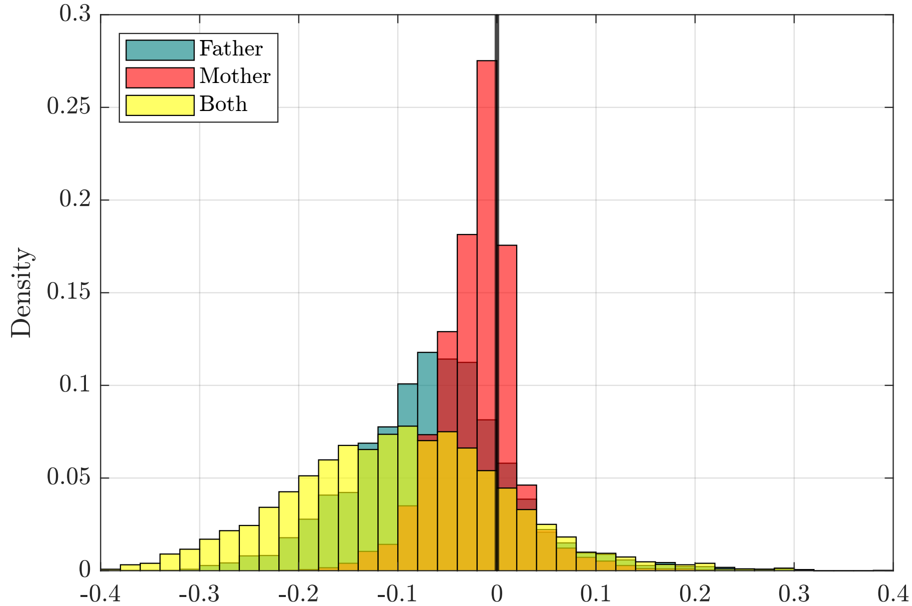
Figure 6: Skill Changes from Increasing Tax Progressivity
(Skill Change vs. Income Level)



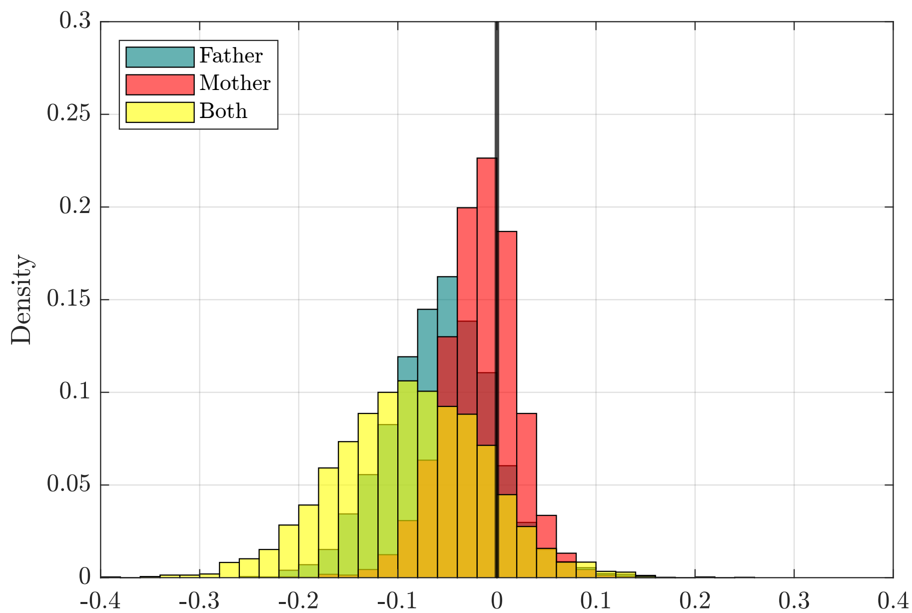
Notes: This figure plots final skill changes compared to the baseline after increasing tax progressivity. Each dot represents a simulated household. The x-axis plots the log average annual post-tax income at the household level, and the y-axis plots the change in the child final skill measured in the unit of the standard deviation in the baseline.

Figure 7: Distributions of Skill Changes to a Mean-Preserving Spread in the Wage Offer Shock with a More Progressive Tax-and-Transfer System

(a) Baseline (Reproduced)



(b) Progressivity Tax Experiment

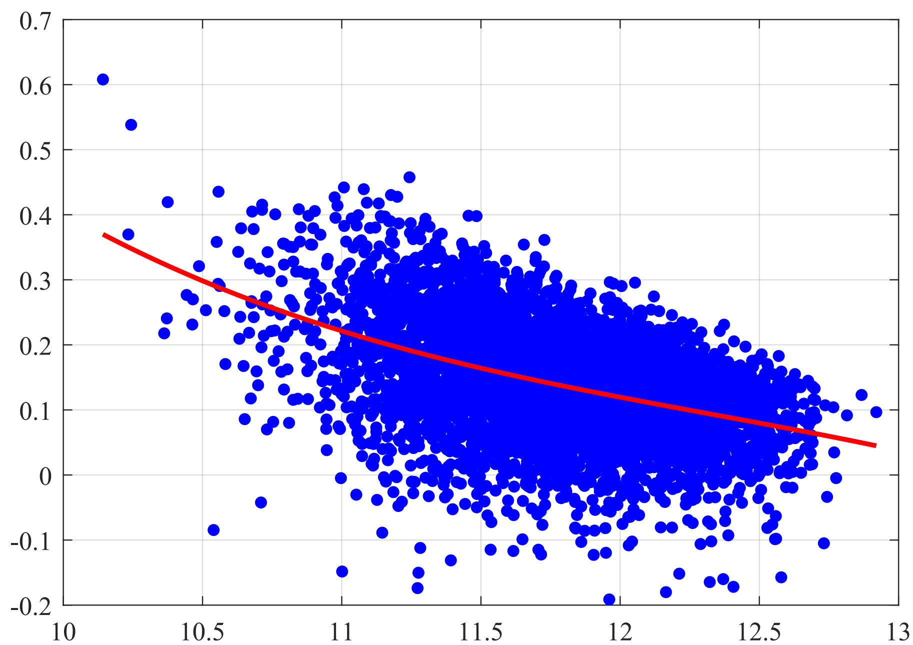


Notes: This figure plots the distribution of skill changes, measured as a ratio of the standard deviation of skills in the baseline, to a larger (50% more compared to the baseline) father wage offer shock (blue), mother wage offer shock (red), and both (yellow).

6.2.2. Universal Basic Income

We implement Andrew Yang's proposal of a universal basic income of \$1,000 per month for every American adult over the age of 18. This amount to \$24,000 a year for a two-parent household in our economy, or \$48,000 for two years (one model period). We introduce UBI while keeping the tax system unchanged. That is, we set χ_3 such that even if a household has no labor income it can get such amount of UBI, while keeping χ_1 and χ_2 unchanged. Appendix Figure C.2 shows that the introduction of UBI shifts upward the relationship between pre- and post-tax income. In this experiment, UBI is unfunded and we do not adjust taxes to finance it.

Figure 8: Skill Changes from Introducing UBI
(Skill Change vs. Income Level)



Notes: This figure plots final skill changes compared to the baseline after the introduction of UBI. Each dot represents a simulated household. The x-axis plots the log average annual post-tax income at the household level, and the y-axis plots the change in the child final skill level measured in the unit of the standard deviation in the baseline.

Figure 8 plots final skill changes compared to the baseline after the introduction of UBI. Each dot represents a simulated household. The x-axis plots the log average annual post-tax income at the household level, and the y-axis plots the change in the child's final skill measured in the unit of the standard deviation in the baseline. In contrast to the results from the tax progressivity experiment in Figure 6, the introduction of UBI raises (on average) children's skill levels across the income distribution (red line). For example, we see the highest impact on children's skills for the lower end of the income distribution, amounting to approximately an increase of 0.3 standard deviations. This impact fades out for higher-income families as the incidence of the UBI transfer naturally decreases in higher-income families.

We highlight that such positive effects on children skills are not hard-wired in the model. In fact, children could possibly suffer from the UBI. For example, parents who reduce their labor supply, to work (discretely) less and earn a smaller amount in total could be forced to reduce child-related expenditures. The data points illustrating negative effects in Figure 8 highlight the unintended consequences of UBI. This outcome is particularly notable for children coming from the higher-end of the income distribution and results from behavioral responses in time and monetary inputs for child development caused by UBI. These adverse effects emerge even though the UBI policy experiment does not involve raising taxes nor redistributing resources from higher to lower-income families. Finally, although our findings suggest positive impacts on the overall skill levels of children from lower-income families, Appendix Figure C.3 shows that the effect on intergenerational mobility, measured by the rank-rank relationship between family income and children's skills, is negligible.

7. Conclusion

This paper aims to quantify the mechanisms and the extent to which parental wage risk passes through to children's skill development. Through the lens of a quantitative model of labor supply in which both parents choose how many hours to work, time spent with children, and child-related expenditures, we find that income risk slows down skill accumulation, permanently lowering children skill levels. Parents' wage risk has a scarring effect on children's skills. To the extent that making up for such skill losses during childhood is hard, as the available evidence suggests, uninsurable income risk can negatively impact the labor market prospects of future generations. Income risk affects relatively more low-income households with limited ability to adjust labor supply in the face of negative wage shocks. A more progressive tax-and-transfer system can attenuate children's skill losses.

Lastly, we would like to acknowledge potential limitations of our study that could lay the groundwork for future research. First, in a study by Daruich (2022), a general equilibrium model of overlapping generations was employed to assess the long-term impacts of large-scale early childhood policies. The calibrated model reveals that these policies have more substantial effects than previously estimated. The key mechanism behind these amplified effects is the realization that today's higher-achieving children will become tomorrow's better parents. Consequently, policies aimed at enhancing the skills of children hold the potential to have a lasting impact for generations to come. While our model does not lend itself to quantifying these multi-generational effects of policy, these results imply that our findings likely represent a conservative estimate of the impacts of income risk and limited insurance.

Also, our quantitative analysis is silent about the optimal tax and transfer system that could mitigate the adverse consequences of wage risk for the next generation. Although this exercise falls beyond the scope of this paper, our estimates regarding the technology of skill formation could serve as a basis for future research on the topic.

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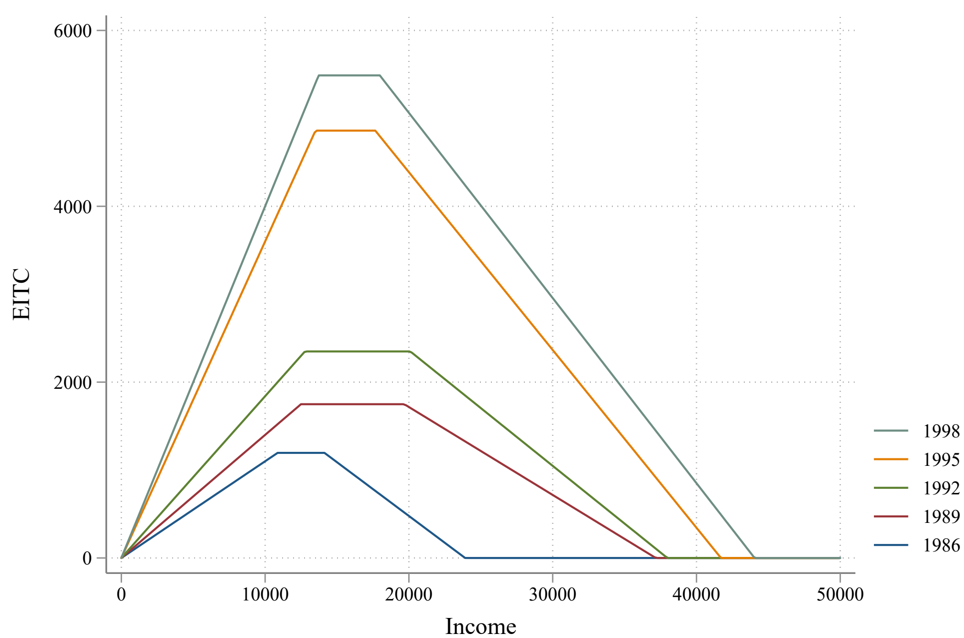
Appendix

A. The Earned Income Tax Credit

The Earned Income Tax Credit (EITC) was initially established in 1975 to supplement the earnings of working families. Since then, it has undergone several expansions by the federal government, with the most significant expansions in 1986, 1993, and 2009, and has become one of the largest income support programs in the US. Refer to Hotz and Scholz (2003) and Nichols and Rothstein (2016) for a description of the EITC program and an extensive review of the literature on the impact of the program and its reforms.

Eligibility for the EITC is contingent on having a dependent child, earning a positive income and an adjusted gross income below a certain limit, which varies across time and the number of dependent children. The EITC benefit structure has an initial phase-in offering a proportional subsidy on earnings, a plateau with a constant benefit, and a phase-out where benefits decrease. Figure A.1 illustrates how the EITC schedule looks like for the Federal EITC for families with two children in selected years. In this paper, we consider a household's total EITC benefits as the sum of federal and state EITC credits.

Figure A.1: Federal EITC Schedules for Families with Two Children (in 2015 Dollars)



Notes: The figure plots the the federal Earned Income Tax Credit as a function of earned income for families with two children in selected years. Amounts are expressed in 2015 US dollars.

B. Data

B.1. National Longitudinal Study of Youth 1979 (NLSY79) and Children (NSLY79-C)

The National Longitudinal Study of Youth 1979 (NLSY79) comprises a representative sample of teenagers and young adults in the United States in 1979. Information is collected through longitudinal surveys. Interviews were conducted annually until 1994 and biennially thereafter. For respondents from the original sample who became mothers during the study, the research also collects data about their children (NSLY79-C). Our sample is formed by matching the sample of mothers with the sample of children, encompassing demographic details of participants and their family members. Additionally, it includes information about income, employment status, and hours worked for both mothers and their spouses.

The study also includes information about the cognitive development of children aged five years and older. These cognitive measures are collected through achievements in math and reading test scores every other year, starting from 1986. Specifically, the study provides details about the Peabody Individual Achievement Test (PIAT), a series 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).

B.2. Consumer Expenditure Survey

Collected by the US Bureau of the Census and sponsored by the Bureau of Labor Statistics, the CE is representative at the national level. The dataset is a rotating panel that covers approximately 5,000 households per year over four consecutive quarters. For our analysis, we focus on surveys from 1996 onward due to considerations of data availability and measurement precision.

The CE comprises an interview section and a diary section. The interview is conducted quarterly with each household unit, tracking significant expenditures. The diary section aims to capture smaller everyday expenses that are more likely to be overlooked in the interview. The diary is conducted over two consecutive one-week periods with each respondent. The interview and diary sections operate independently. Given the focus of our analysis on substantial child-related expenses, we exclusively consider the interview section of the data.

B.3. American Time Use Survey

The ATUS is a dataset of US national time-diary samples. Implemented in January 2003, ATUS has since been conducted as an ongoing monthly survey sponsored by the Bureau of Labor Statistics. It serves as a time-use dataset for a representative sample in the US, collecting data within a 24-hour period for one respondent from each household. We extract the data from IPUMS (Flood, Sayer, and Backman, 2022).

We limit our sample of interest to households with one or more children. However, due to data limitations, precise identification of parents and children is impossible. To address this, we apply a straightforward and reasonable rule: we exclude respondents younger than 18 years old from the sample and utilize gender information to distinguish between the father and the mother. The age distribution data reveal a bunch within the sample of married households with children, particularly in the respondent's age range of 15-17. This cluster represents approximately 9 percent of the sample, while the percentage for the age range 18-20 is negligible, accounting for about 0.5 percent. This evidence suggests that, with some exceptions, individuals in the 15-17 age group are typically considered "children" in the household rather than parents.

C. Additional Tables and Figures

Table C.1: Descriptive Statistics: Parental Expenditures

	Whole Sample		Married Sample	
	Mean (1)	St.Dev. (2)	Mean (3)	St.Dev. (4)
Expenditures:				
Child expenditure	753.55	1553.23	850.55	1725.15
Non-durables	6728.39	3697.18	7279.55	3828.45
Childcare	295.80	882.82	334.92	970.56
Child clothes	219.98	313.79	230.73	322
Education	36.297	189	41.76	196.25
Tuition	132.05	1094.66	165.32	1246.83
Toys	69.42	216.10	77.82	234.86
Demographics (respondent):				
Number of children	1.84	0.96	1.88	0.95
Female	0.53	0.50	0.42	0.49
Age	39.69	10.16	40.02	9.25
Married	0.72	0.45	1	0
Black	0.14	0.35	0.08	0.28
Other non-white background	0.07	0.26	0.08	0.28
Less than high school completion	0.15	0.36	0.13	0.33
High school completion	0.26	0.44	0.23	0.42
Some college	0.30	0.46	0.29	0.45
College graduate	0.29	0.45	0.35	0.48
Observations	108,218		78,038	

Notes: The table shows the descriptive statistics for the regression samples used in the analysis of parental expenditures. Expenditures are measured quarterly and expressed in year 2016 dollars.

Table C.2: Descriptive Statistics: Parental Time Use

	Whole Sample		Married Sample	
	Mean (1)	St.Dev. (2)	Mean (3)	St.Dev. (4)
Time Use:				
Work	190.76	263.04	215.10	275.33
Childcare	84.69	116.65	103.98	123.05
Leisure	1164.55	272.05	1120.92	272.61
Demographics (respondent):				
Female	0.59	0.49	0.56	0.50
Age	32.27	8.94	35.78	5.97
Married	0.66	0.47	1	0
Black	0.09	0.29	0.05	0.22
Other non-white background	0.06	0.24	0.06	0.24
Less than high school completion	0.22	0.41	0.09	0.28
High school completion	0.23	0.42	0.24	0.43
Some college	0.17	0.38	0.17	0.38
College graduate	0.38	0.48	0.50	0.50
Observations	46,301		30,457	

Notes: The table shows the descriptive statistics for the regression samples used in the analysis of parental time use. Time use is measured in minutes per day.

Table C.3: EITC Expansion and Time Use: Alternative Definition of Program Reform

	(1) Work	(2) Childcare	(3) Leisure	(4) Work	(5) Childcare	(6) Leisure
Program Reform	18.80**	-6.28*	-12.52	0.77	2.15	-2.93
	(7.52)	(3.61)	(7.57)	(6.13)	(3.40)	(6.89)
Observations	16,829	16,829	16,829	29,472	29,472	29,472
MeanDep.Var.	167.91	80.11	1191.98	203.8	87.31	1148.88
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Policy Exposure	High	High	High	Low	Low	Low
Sample	Whole	Whole	Whole	Whole	Whole	Whole

	(1) Work	(2) Childcare	(3) Leisure	(4) Work	(5) Childcare	(6) Leisure
Program Reform	18.81	-6.94	-11.87	-2.32	3.85	-1.53
	(11.83)	(6.00)	(12.47)	(7.31)	(3.98)	(8.33)
Observations	8,523	8,523	8,523	21,934	21,934	21,934
MeanDep.Var.	186.35	94.61	1159.04	226.28	107.62	1106.1
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Policy Exposure	High	High	High	Low	Low	Low
Sample	Married	Married	Married	Married	Married	Married

Notes: The table shows the effect of changes in the EITC program on parental time use. Dependent variables: work time (columns 1 and 4), childcare time (columns 2 and 5), and leisure time (columns 3 and 6). Individuals with a family income below 110 percent of the state-year specific EITC income threshold are considered to have high exposure to the program. The upper panel considers the whole sample. The bottom panel restricts the sample to married individuals. The Program Reform is the coefficient for an indicator variable for prominent changes, at least $150 difference in maximum available benefits, in the EITC schedule. The indicator is equal to 0 until the first prominent change in state s where individual i resides, and equal to 1 for all later years. Time use is measured in minutes per day. Individual controls include respondent's education background (less than high school completion, high school completion, some college, college graduate), marital status, race, gender, age and age squared. Standard errors clustered at the state level are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. See text for further details on the analysis.

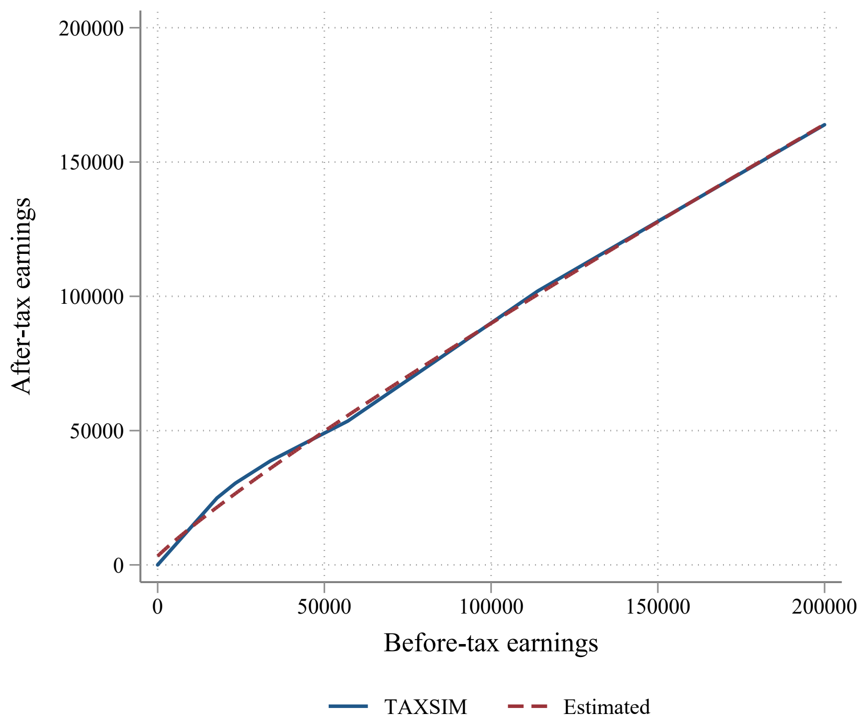
Table C.4: EITC Expansion and Time Use: Alternative Definition of Exposure to the EITC

	(1) Work	(2) Childcare	(3) Leisure	(4) Work	(5) Childcare	(6) Leisure
Program Reform	15.96**	-8.92**	-7.04	4.73	-1.58	-3.15
	(7.41)	(3.99)	(7.88)	(6.53)	(3.10)	(7.20)
Observations	15,161	15,161	15,161	31,140	31,140	31,140
MeanDep.Var.	165.65	80.29	1194.05	202.98	86.84	1150.18
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Policy Exposure	High	High	High	Low	Low	Low
Sample	Whole	Whole	Whole	Whole	Whole	Whole

	(1) Work	(2) Childcare	(3) Leisure	(4) Work	(5) Childcare	(6) Leisure
Program Reform	22.94*	-9.79	-13.15	0.38	-0.94	0.56
	(12.29)	(6.36)	(13.12)	(8.35)	(3.52)	(9.20)
Observations	7,479	7,479	7,479	22,978	22,978	22,978
MeanDep.Var.	184.19	94.23	1161.58	225.17	107.15	1107.68
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Policy Exposure	High	High	High	Low	Low	Low
Sample	Married	Married	Married	Married	Married	Married

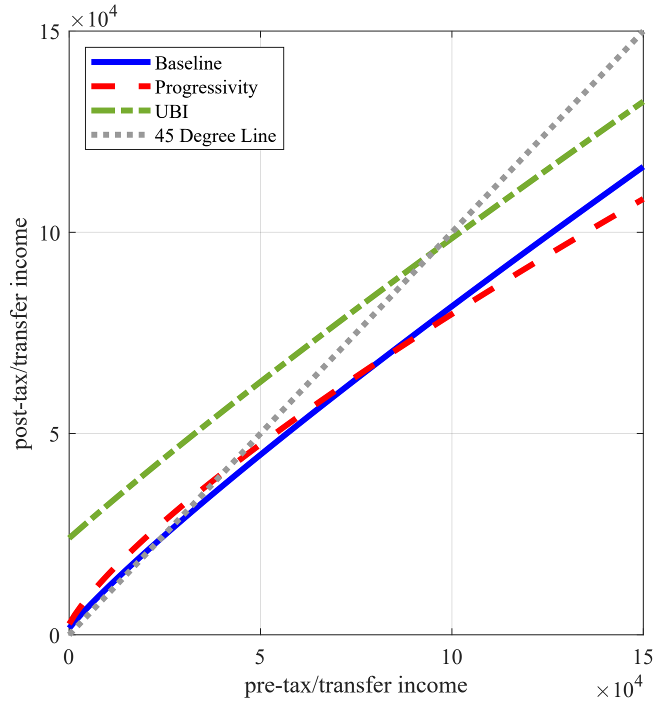
Notes: The table shows the effect of changes in the EITC program on parental time use. Dependent variables: work time (columns 1 and 4), childcare time (columns 2 and 5), and leisure time (columns 3 and 6). Individuals with a family income below 100 percent of the state-year specific EITC income threshold are considered to have high exposure to the program. The upper panel considers the whole sample. The bottom panel restricts the sample to married individuals. The Program Reform is the coefficient for an indicator variable for prominent changes, at least $150 difference in maximum available benefits, in the EITC schedule. The indicator is equal to 0 until the first prominent change in state s where individual i resides, and equal to 1 for all later years. Time use is measured in minutes per day. Individual controls include respondent's education background (less than high school completion, high school completion, some college, college graduate), marital status, race, gender, age and age squared. Standard errors clustered at the state level are reported in parentheses. *, **, *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively. See text for further details on the analysis.

Figure C.1: Tax System



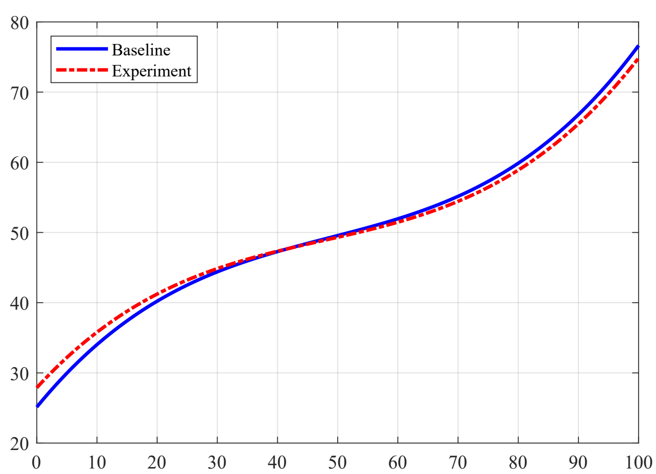
Notes: This figure illustrates the good fit of the parametric tax function. The blue solid line is the data from TAXSIM, and the red dashed line is the estimated tax function.

Figure C.2: Comparing Tax Systems



Notes: This figure plots the tax functions in the baseline model that is estimated from data (blue), in the experiment of a more progressive tax system considered in Section 6.2.1 (red), and in the UBI experiment considered in Section 6.2.2 (green), together with the 45-degree line for reference (gray).

Figure C.3: Intergenerational Mobility



Notes: This figure shows the measurement (rank-rank) of intergenerational mobility for baseline economy (blue solid line), and counterfactual economy under the new Universal Basic Income policy regime (red dashed line). The x-axis plots the rank of average family income over the child's life cycle, while the y-axis plots the rank of children's skills in the last period (age 13-14).

D. Standard Errors of the Model's Parameters

We estimate the model via the simulated method of moments (SMM) estimator. The estimator of our model can be written as

$$\begin{aligned}\widehat{\Omega} &= \arg\min_{\Omega}(M^{data} - M^{Sim}(\Omega))'(M^{data} - M^{Sim}(\Omega)) \\ &= \arg\min_{\Omega} g(\Omega)' g(\Omega)\end{aligned} \tag{D.1}$$

Under standard conditions, the Central Limit Theorem states that:

$$\sqrt{N}(g(\Omega_0) - 0) \xrightarrow{d} N(0, Q_0)\,,$$

where Ω_0 represents the vector of true population parameters, while Q_0 represents the population variance-covariance matrix of the moment conditions. For N large enough, the vector of moment conditions is asymptotically normal distributed $g(\Omega_0) \overset{a}{\sim} N(0, \Psi)$, where $\Psi = \frac{Q_0}{N}$. Under the central limit theorem, the SMM estimator follows the following limiting distribution:

$$\sqrt{N}(\widehat{\Omega} - \Omega_0) \xrightarrow{d} N(0, (G_0'G_0)^{-1}G_0'Q_0G_0(G_0'G_0)^{-1})\,,$$

where $G_0 = \nabla_{\Omega}\, g(\Omega_0) \equiv \nabla_{\Omega}\, M^{Sim}(\Omega_0)$ represents the Jacobian matrix of the simulated moments with respect to the model's parameters. Our SMM estimator is distributed asymptotically normal:

$$\widehat{\Omega} \overset{a}{\sim} N(\Omega_0, \Sigma)\,,$$

where $\Sigma = (G_0'G_0)^{-1}G_0'\Psi G_0(G_0'G_0)^{-1}$. The empirical counterpart of the variance-covariance matrix of the SMM estimator ($\widehat{\Sigma}$), used for computing the standard errors of the model's parameters, is derived by evaluating numerically the Jacobian matrix at the estimate $\widehat{G} = \nabla_{\Omega}\, M^{Sim}(\widehat{\Omega})$. Additionally, it incorporates the estimated variance-covariance matrix of the data moments ($\widehat{\Psi}$), obtained via the nonparametric bootstrap method. Given that our moments are constructed from three independent datasets (NLSY, CEX, and ATUS), we independently estimate the variance-covariance matrix of the data moments for each dataset. Subsequently, we enforce independence of moments across the three datasets to construct the final variance-covariance matrix of the data moments.