Understanding the Effects of Workfare Policies on Child Human Capital*

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Abstract

Workfare policies might have negative effects on children's development by inducing parents to spend less time at home. I study the mechanisms by which workfare policies affect children using the workfare experiment "New Hope" (Milwaukee, 1994-1997). The program randomly assigned an earnings subsidy and a child care subsidy subject to a full-time work requirement. For families with young children, the program had sizable, positive effects on child academic performance. Counterfactual experiments from a dynamic-discrete choice model indicate that most of the effect of New Hope on child human capital is explained because parents enrolled their children in center-based child care.

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1 Introduction

To promote the labor market participation of individuals from low socioeconomic backgrounds, policymakers have implemented welfare policies that induce, or directly require, working more hours—also known as "workfare" policies. Two types of policies are often found to be common in many countries: wage and child care subsidies. In the U.S., prominent examples of such workfare policies are the Earned Income Tax Credit (EITC) and the Child Care Development Fund (CCDF).[1] Even though one of the main goal of workfare policies is to incentivize work,[2] they could have unintended, negative consequences on child outcomes: parents can increase the time spent in the labor market and reduce the time caring for children.[3] This possibility can undermine the original motivation for welfare in the first place: to provide aid for economically disadvantaged children.

This paper analyzes how workfare policies can affect human capital development in the early years. To identify the reduced-form effects of workfare policies on children, I use data from the experimental workfare program "New Hope." Implemented in Milwaukee (1994-1997), the program offered both wage and child care subsidies as a single policy bundle, having positive effects on child academic achievement. However, because all of New Hope policies were bundled together into one random assignment, we cannot assess the role that individual policies and household-level inputs played in producing child human capital. To deal with this lack of identification, I exploit both experimental and quasi-experimental variation—coming from different workfare policies—to estimate a dynamic structural model of the household and child human capital. With this framework, I study which type of workfare policy affects child human capital the most and what are the household-level mechanisms that explain these effects. The combination of experimental and structural approaches yields lessons that are relevant to the design and evaluation of workfare policies.

[1] For further details on these and other mean-tested programs, see Moffitt (2003) and Moffitt (2016).

[2] See Grogger and Karoly (2009) and Moffitt (2016) for a review of the evidence. See Hoynes and Rothstein (2016) and Nichols and Rothstein (2016) for a description of the EITC and its impacts on labor supply. See also Chan (2013) and Keane and Wolpin (2010) for an analysis of the impact of changes in the welfare system on recipient's labor supply and income.

[3] See Bernal (2008), Bernal and Keane (2010), Bernal and Keane (2011), Brilli (2014), and Agostinelli and Sorrenti (2018) for evidence comparing the effects of parental income and time allocation on child development. See Heckman and Mosso (2014) for a review of the evidence on the effects of income on skills accumulation over the child life-cycle.

New Hope experimentally tested the effects of two of the most common workfare reforms: wage and child care subsidies. The program randomly assigned applicants (over 18 years old) to a workfare policy bundle that included an earnings subsidy—similar to the EITC—and a child care subsidy—which resembled the CCDF. Furthermore, to have access to any of these benefits, participants had to prove having worked full time in a given month. Given its similarity to well-known workfare policies implemented in the U.S., New Hope represents an ideal laboratory to study the potential effects of large-scale workfare policies that have been implemented in the U.S. and elsewhere on family and child outcomes (Bos et al., 1999; Huston et al., 2001, 2005).

I start by showing that access to New Hope had relatively large effects across various family outcomes and that these effects are mainly concentrated among families with young children. For women with children in their preschool years while New Hope was in effect, the program increased annual family income by 13%, the probability of being employed in any given quarter by 8 percentage points (from a baseline of 67%), and the likelihood of using child care for young children by 22 percentage points (from a baseline of 40%). Notably, the program had a sizable, positive effect on a measure of academic performance of children (0.46 standard deviations). Effects for parents and children are much larger in magnitude that those equivalent for parents of older children (which are mainly statistically insignificant). Evidence on heterogeneous effects by child age is a novel finding to the New Hope and welfare experiments literature (Huston et al., 2001, 2005; Grogger and Karoly, 2009; Huston et al., 2011).[4]

To explore the mechanisms leading to these reduced-form effects, I exploit experimental and quasi-experimental variation to build and estimate a structural model of household choices and child human capital. In the model, a single-child unitary household chooses hours of work and child care types (informal home care or formal, center-based child care). The child human capital technology follows a dynamic process, where household decisions and the current stock of child human capital are inputs that produce next-period human capital. The household's budget set incorporates different elements of the social safety net, including the

[4]Similarly, Michelmore and Pilkauskas (2020) document that most of the labor supply effects of EITC shocks are concentrated among women with children under age three.

AFDC, Food Stamps, EITC, CCDF, and New Hope. Identification of the model exploits the random assignment of New Hope as well as other policy shocks coming from large shifts in the U.S. social policy: changes in the EITC schedule, the introduction of TANF as a replacement of AFDC, and the implementation of the CCDF.

My counterfactual exercises reveal that center-based child care has a pivotal role when accounting for the effects of New Hope on child human capital. The child care subsidy explains most of the effects of New Hope on child human capital: the effect of the child care subsidy on child human capital is 100% larger than that of the wage subsidy. The full-time work requirement has a negative effect on child human capital; the effects of the program would have been larger if New Hope had not included a work requirement. In terms of household choices, almost two thirds of the effect of New Hope on children is explained because parents, induced by the program, enrolled their children in center-based child care. If New Hope had included only a wage subsidy (without work requirements), the human capital effects would have been explained mostly by the fact that household had more money (net of child care expenditures). Even so, 40% of the effect of this hypothetical policy on child human capital can be attributed to a higher use of center-based child care.

This paper contributes to the literature on welfare reforms and children outcomes by formally quantifying the household- and policy-level mechanisms explaining reduced-form effects. Various papers report effects of the EITC effects on test scores, high-school and college completion, employment, earnings, and even health (Maxfield, 2013; Hoynes et al., 2015; Bastian and Michelmore, 2018; Manoli and Turner, 2018; Michelmore and Pilkauskas, 2020). On the other hand, Herbst and Tekin (2010), Hawkinson et al. (2013), and Herbst and Tekin (2016) study the effects of the CCDF child care subsidies on child outcomes, finding negative effects on child outcomes.[5] As Nichols and Rothstein (2016) point out, it is tempting to attribute the effects of a particular reform to changes in one particular household variable. For example, one potential interpretation of the positive reduced-form effects of EITC exposure comes from the causal effects of having more income on child outcomes (Dahl and Lochner, 2012; Agostinelli and Sorrenti, 2018; Nicoletti et al., 2020).

[5] See Elango et al. (2016) and Hotz and Wiswall (2019) for a review of the evidence of more general child care policies.

Equivalently, one could speculate that the association between child care subsidies and child outcomes is due to child care "quality" (Hotz and Wiswall, 2019). However, in both examples, workfare policies affect children indirectly by changing parents decisions in many dimensions (Moffitt, 2003, 2016; Chan and Moffitt, 2018). Therefore, absent multiple sources of external variation, reduced-form evidence is unable to quantify the importance of different household-level mechanisms explaining treatment effects. Furthermore, as in the case of the U.S., large-scale welfare policies—such as the TANF, EITC expansions, and the establishment of the CCDF— have been implemented almost contemporaneously, which might obscure the interpretation of—or directly bias—the reduced-form estimated effect of any individual policy.[6] Similarly, Grogger and Karoly (2009) speculate that the varied results coming from several workfare RCTs may be explained by the different types of policies that each program considered. In the context of New Hope, my paper studies the mechanisms through which EITC-like and child care subsidies affect child human capital while isolating the individual contribution of each policy. In doing so, I establish a significant role for child care choices and child care polices as the key underlying mechanisms. This conclusion is consistent with a literature that finds sizable impacts of child care subsidies and enrollment on children from low-income families (Havnes and Mogstad, 2011, 2015; Kline and Walters, 2016; Herbst, 2017; Cornelissen et al., 2018; Felfe and Lalive, 2018).

This paper is also connected to a literature that studies the effects of welfare reform on families using structural models. Bernal (2008), Del Boca et al. (2013), Mullins (2019), Verriest (2018), and Chaparro et al. (2020) estimate dynamic models of parental choices and child human capital, making important contributions to the literature on public policies and the development of child human capital. My paper contributes to such literature in developing a model that successfully replicates treatment effects of policy-relevant counterfactual experiments, providing a credible framework to understand underlying mechanisms explaining the effects of workfare policies on families. Specifically, my structural approach differs with respect to the literature in three aspects. First, I model both the welfare system and random assignment to New Hope to analyze the effects of household choices and child

[6] See Kleven (2019) for a related critique in the identification of the reduced-for effects of EITC expansions on female labor supply.

outcomes of actual public-policy shocks, within a realistic economic environment.[7] Second, I exploit both experimental and quasi-experimental variation in estimation and validate the model's predictions with experimental effects. I show that my model is able to reproduce experimental-based treatment effects estimates on key variables. Third—except for Verriest (2018) who analyze the effects of divorce on child outcomes—most papers do not consider child care as part of the choice space, which turns out to be an important driver of my results regarding child outcomes.

The remaining of the paper is structured as follows. Section 2 describes the New Hope program's characteristics. Section 3 provides details on the available data and sample selection. Section 4 outlines the available reduced-form evidence on New Hope. Section 5 presents the dynamic-discrete choice model and Section 6 discusses its estimation. Section 7 shows the model's estimates and explains its implications for the dynamics of skills acquisition. Finally, Section 8 assesses the consequences of income and child care subsidies on household decisions and child outcomes.

2 The New Hope welfare model and context

Inspired by the welfare debate that dominated the policy agenda in the 90s, New Hope was designed to promote the transition from welfare to work. As a result, the program greatly enhanced existing work incentives.[8]

Applicants living in Milwaukee, Wisconsin, were recruited in two economically disadvantaged neighborhoods.[9,10] To be eligible, individuals had to be at least 18 years old and had a household income less than or equal to 1.5 times the federal poverty line.[11] Additionally,

[7]Recently, Mullins (2019) incorporates the welfare system in a discrete-choice model to study the effects of different policies on mother's welfare and child human capital. His analysis differs from mine in that policies of interest are different. Additionally, his paper does not focus on the potential mechanisms explaining the predicted effects of welfare policies.

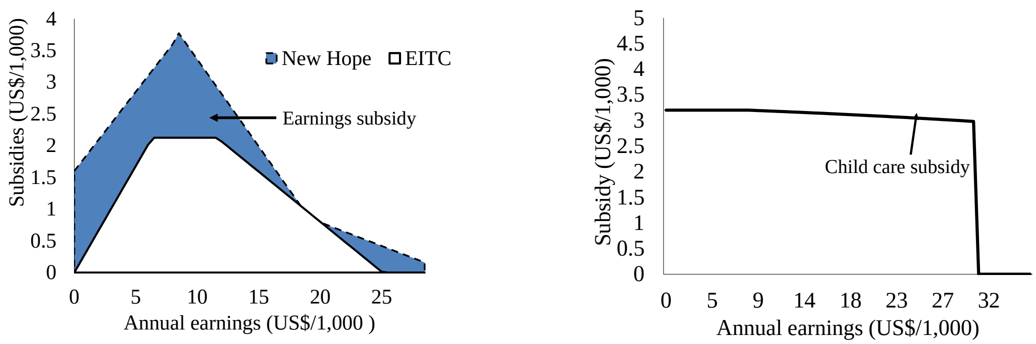
[8]Later on, many of the policy changes in the U.S. were similar to the New Hope package. See for example Moffitt (2003).

[9]Applicants came from the north and south side of the U.S. Highway 94 and the Menomenee River Valley. The New Hope team selected those neighborhoods (which were defined by their postal zip codes) because they had a relatively high poverty rate and ethnically diverse populations. Each area had about 40,000 residents (Bos et al., 1999).

[10]New Hope was heavily promoted during the eligibility period. The New Hope team advertised the program in posters, radio, TV, and newspapers, and sent personal letters. About 20% of potential participants in the target areas became aware of the program (Brock et al., 1997).

[11]For a household with one adult and two children, the federal poverty threshold was $12,278. For a

Figure 1: New Hope earnings subsidy and child care subsidy



(a) earnings subsidy

(b) Child care subsidy

Notes: Panel (a) compares the New Hope and EITC design as a function of annual earnings. The solid line shows the EITC earnings subsidy. The difference between the dashed and the solid line represents the New Hope supplement, for each level of earnings, assuming no work requirement. Panel (b) illustrates the child care subsidy design (represented in the solid line). For this figure, the child care cost equals 3,600 dollars a year.

applicants had to be willing to work at least 30 hours per week (which was considered full-time employment for the purposes of accessing the program's benefits). Beginning at baseline recruitment and lasting for 36 months, a randomly selected group of applicants had access to various benefits.[12] In this paper, I focus on three elements of the New Hope package: the earnings subsidy, child care subsidy, and work requirement. Next, I describe these three components and leave the description of the other components of New Hope for Appendix A.

2.1 The earnings subsidy

Figure 1, panel (a), illustrates the earnings subsidy design for a family with one earner and one child.[13] To show how the schedule looks across the distribution of ex-ante labor earnings, the figure assumes no work requirements.[14] The New Hope earnings subsidy complemented the EITC subsidy—that is, the New Hope subsidy is positive as long as the New Hope

single-person household, the threshold was $7,929 (Bos et al., 1999).

[12]Individuals applied to the program during a period of buoyant economic activity. Between 1992 and 1997, job creation at the Milwaukee Primary Metropolitan Statistical Area (which covers the Milwaukee, Washington, Ozaukee, and Waukesha counties) grew by 8.2%. For the same area, the unemployment rate diminished from 4.8% in 1992 to 3.6% in 1997 (Bos et al., 1999).

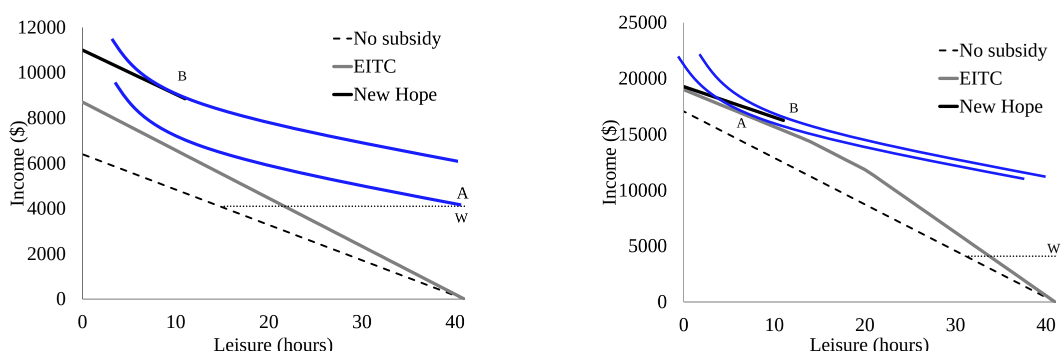
[13]The earnings subsidy corresponds to the sum of two subsidies: an earnings subsidy and a child allowance. Appendix A provides the exact formula of the subsidy.

[14]Even though Figure 1 depicts the earnings subsidy in terms of annual benefits, New Hope beneficiaries received their supplements on a monthly basis. The earnings subsidy was not taxable.

schedule stays above of that of the EITC.[15] Because the earnings subsidy schedule stayed fixed whereas the EITC schedule expanded while the program was running, the treatment "intensity" varied in time.[16]

To evaluate the economic incentives introduced by the earnings subsidy tied to the work requirement, consider two individuals, X and Y, choosing between home and labor market time. For simplicity, suppose that they do not have children and so the child care subsidy option is not relevant. The choices made by X and Y are illustrated in Figure 2, panels (a) and (b). In these graphs, the horizontal and vertical axis show income and time outside the labor market, respectively. Both figures present the individual's budget set under three different cases: without any subsidy, with only the EITC, and under New Hope. Additionally, the figure shows what both individuals would earn if they do not work (at point W).[17] X and Y have the same preference towards income and leisure, and so both have an equal set of indifference curves in the income-leisure plane. The only difference between the budget sets of X and Y is that the wage offer of X is lower than that of Y.

Figure 2: Intensive- and extensive-margin responses to New Hope



(a) Individual X (low wage offer)

(b) Individual Y (high wage offer)

Notes: The figure illustrates extensive- and intensive-margin responses to New Hope. For individuals with two different wage rates and same structure of preferences, it presents individuals choices under different budget sets in the income-leisure plane. Since New Hope requires working 30 hours or more, the New Hope budget set ends at the point of 10 hours of leisure.

[15]In the figure, the dashed line shows a discontinuity at $19,000 because the earnings subsidy is zero at that point while the child allowance continues to phase out.

[16]In graphic terms, the dashed line in Figure 1, panel (a), remained constant, whereas the solid line shifted upwards alongside the changing EITC regulations. These modifications in the EITC meant that the earnings subsidy decreased with time.

[17]I assume this value to be 4,100 dollars, which equals the sum of the average values the control group received one year after baseline from AFDC and Food Stamps (Bos et al., 1999)

All else constant, the figure indicates that the impact of the program on labor supply depends on the wage offer. Without New Hope (if X and Y were in the control group), individuals would allocate at point A. At this point, the wage offer of X is low enough so that she is better off receiving welfare and not working. In contrast, Y would work more than 30 hours a week. If X and Y were in the treatment group, they would choose to allocate at point B. Compared to point A, X would work more hours and receive more income. Y would earn more as well. However, Y works more or less compared to the counterfactual of not having the program, depending on the relative magnitudes of income and substitution effects. Overall, the New Hope earnings subsidy should have a non-negative effect on income and an ambiguous effect on hours worked.[18]

Because the earnings subsidy affects parental time allocation, it can also produce effects on child outcomes. Suppose that labor supply causes a negative effect on child human capital, while income a positive effect (Bernal, 2008; Dahl and Lochner, 2012). Leaving aside the child care subsidy component for a moment, the effect of the earnings subsidy is ambiguous, and depends on the relative strength of intensive- and extensive-margin labor supply responses and the relative productivity of income and time with the child in the production function of child skills.

2.2 The child care subsidy

Figure 1 (panel b) depicts the child care subsidy schedule for the case of a single-child household paying \$3,600 a year for child care, without work requirements. The subsidy amount is stays relatively flat and ends abruptly at a predetermined earnings cutoff. Thanks to the subsidy, families paid a relatively small copayment. Among those who used the child care benefit, the total average cost of child care expenditures was \$9,000 a year, or 74% of the average annual income of the control group at baseline. Following the subsidy formula, New Hope would cover 95% of this cost.[19]

[18] Figures 2a and 2b illustrate one of many situations in which the earnings subsidy impacts labor supply and income. Individual X may choose to stay at point W even with New Hope.

[19] The child care subsidy was used by both preschoolers and school-age children up to 13 years of age. In the case of school-age children, the child care subsidy covered "extended-day programs," that is, after-school care at the child's school or at another center. Both for preschoolers and school-age children, child care centers must have been licensed by the state of Wisconsin.

Economically disadvantaged families had access to a number of child care programs offered by the Milwaukee's welfare department—with reimbursement rates and subsidy limits that were similar to the New Hope design (Brock et al., 1997).[20] However, families in the New Hope program had some clear advantages over families using the public system. First, participation in New Hope increased their chances of finding low-cost child care services. Parents in the public system under AFDC, for example, usually faced long waiting lists to apply for public child care subsidies. For families who were not in the welfare system, finding a low-cost child care provider was even harder (for example, obtaining a Head Start slot was almost impossible).[21] In contrast, New Hope beneficiaries enrolled their children in any of the county- or state-licensed child care centers available in the city. Second, qualitative evidence indicates that families who were eligible for public child care programs struggled to comprehend and navigate Wisconsin's complex system (Bos et al., 1999; Blau, 2003). As New Hope gathered all subsidies into one single program, families under New Hope benefited from a simpler system. Moreover, families could reach out to New Hope representatives whenever they had questions regarding their benefits, or if they could not find suitable child care facilities in the city.

A child care subsidy produces various behavioral changes within the household. Take the case of two individuals ("A" and "B") who would work 30 hours or more with and without the program. Without New Hope, "A" would pay for a child care service while "B" would not. For individual "A", the program only raises her disposable income while for "B" there is an incentive to take up the subsidy to use the child care option. Now consider another individual ("C") who, without New Hope, would work less than 30 hours and not use center-based child care. If she would like to use child care under New Hope, she would have to work more than 30 hours. For this individual, the economic incentive provided by the earnings subsidy may induce her to do so. The child care subsidy affects child human capital for these three individuals through different mechanisms. Suppose that, relative to home care, child care has a positive impact on child human capital. Even though there is no effect on child

[20] Starting 1997, the CCDF enhanced the low-cost child care supply. Furthermore, the State of Wisconsin supplemented the federal funds from the CCDF to make the child care subsidies available to all eligible families. As a result, the public system began to offer a very similar service to that of New Hope, making the relative gain of the latter system much smaller after 1997.

[21] 54% of the New Hope full sample were not under AFDC (Bos et al., 1999).

care take-up for individual A, her child would benefit from the child care subsidy because A has more income. In contrast, as child care is more productive than home care, individual B's child can benefit from the center-based child care if B chooses this option. One could find a negative effect of the child care subsidy in the case of individual C: because she has to work full time in order to take up the child care subsidy, the impact on child human capital depends on the productivity of child care relative to that of labor supply in the human capital technology. Therefore, as with the earnings subsidy, theory does not give a clear prediction on the sign of the effect of the child care subsidy on child outcomes.

2.3 The work requirement

To receive any of the subsidies of the program in a given month, the participants had to show having worked 30 hours a week on average. To enforce this requirement, New Hope agents asked applicants for the last month's wage stubs. After reviewing those wage stubs, New Hope representatives would determine the amount of supplement that the participants were to receive. This process usually lasted 15 days. After this period, the participant would receive the payment by approximately the 20th of the same month.

Introducing a work condition into a welfare program can impact household behavior and therefore child human capital. Suppose an individual working part-time under a workfare policy with no work requirements. Since working full-time is costly (reduced leisure time) she might not be willing to accept this condition, which leave her without accessing the income and child care subsidy. Alternatively, the benefits coming from these subsidies can more than compensate the associated cost of working full time. Therefore, the effects of introducing a work requirement to a workfare policy on labor supply, income, and child care use are ambiguous.

3 Data

To evaluate the intervention's impact, data on participant's labor market outcomes and families up to eight years after baseline was collected. This section how I use available data to construct key variables used in the reduced-form and structural estimation. I also discuss sample selection procedures.

3.1 Data sources

Labor market outcomes. To construct family income, I combine information from surveys and administrative records. Data on quarterly earnings comes from Wisconsin's Unemployment Insurance (UI) database. Other sources of administrative data include the money equivalent of Food Stamps and AFDC cash transfers (or TANF depending on the period). In addition, I observe New Hope cash payments, from the earnings subsidy and community service job payments. Finally, to have a better measure of income and to correctly compute New Hope subsidies in the counterfactual exercises, I simulate EITC payments taking into account how the EITC schedule has shifted throughout the period. I impute EITC payments assuming a 100% take-up. For the reduced-form analysis, I compute annual family income as the sum of all of these sources, starting baseline year up to eight years after. Other sources of income are not available, such as the WIC or the child tax credit. In addition, New Hope surveys from two years after baseline have spouse's earnings, information which I incorporate in the main structural estimation.

I consider two labor supply variables. The first is quarterly employment, and it is defined as having a positive UI or CSJ earnings record in a given quarter. Nevertheless, the estimation of the dynamic model needs additional information on hours worked. To this end, I use New Hope surveys in combination with quarterly employment to define hours worked for three periods: two, five, and eight years after baseline.

Child care. I construct the child care variable using the New Hope surveys. In the second-year survey, individuals were asked about all regular child care arrangement for the past two years. Possible child care arrangements in the survey are: (i) Head Start; (ii) preschool, nursery school, or a child care center other than Head Start; (iii) school-based extended day program; (iv) another child care other than in someone's home; (v) a person other than a member of the household; (vi) another member of the family of household; and (vii) no arrangements. Participants reported the number of months spent in each case (except for number (vii)). I consider a formal child care arrangement categories (i)-(iv), and an informal child care the rest of them. I define $cc_t = 1$ if the child (as declared by the parent) spent the maximum number of months in categories (i)-(iv) and 0 otherwise.

Child outcomes I use the Social Skills Rating System, Academic Subscale, to have a measure of child academic achievement. This variable can be obtained using teachers' answers to ten questions about how the child performs in the classroom.[22] The variable is constructed based on a score over these ten items: overall performance, reading, math, reading grade expectations, math grade expectations, motivation, parental encouragement, intellectual functioning, classroom behavior, and communication skills. In each of these ten items, the teacher is asked to rank the child in five-point scale measuring the relative position of the child in the classroom academic achievement distribution.[23] The scale is defined as follows: 1 (bottom 10%), 2 (next lowest 20%), 3 (middle 40%), 4 (next highest 20%), and 5 (highest 10%). These data were collected for children aged 5 to 12, who were at least in primary school.

3.2 Sample selection

In my analysis, I exploit data from two samples. First, I use data on applicants with at least one child at baseline. This sub-sample is referred as the Child and Family Study (CFS). The CFS has information only for participants with at least one child between 1 and 10 years of age at baseline. Out of the original $1,357$ baseline sample, 641 adults have at least one child.[24] My reduced-form estimates and structural framework uses data only for the 585 women of the CFS sample and their 904 associated children (where, some of these children have missing SSRS measures).

For my counterfactual exercises, I focus on the sample of adults with children who were six years of age or less by two years after random assignment. This choice serves for two purposes. First, it captures children who were young enough to have used the child care

[22] Teachers were informed about the fact that children were participating in a study related to families and children but they did not know about New Hope, or that they were being assessed as a part of the New Hope evaluation.

[23] See Gresham and Elliot (1990) for details.

[24] Up to two children per family were selected to be part of the CFS. According to Miller et al. (2008), if more than two children were potentially eligible to participate in the CFS survey, only two of them were randomly chosen (with preference given to opposite-sex siblings).

subsidy for an early childhood child care center. In contrast, older children (up to ten years of age) may have used the subsidy to purchase after-school care services. Arguably, the production of human capital under child care and after-school care is not the same and this paper focuses on the impact of being in a early childhood child care center. Second, since test scores were only available for school age children (and for a few children in kindergarten), working with six-year-old children allows me to recover test scores for five- and six-year-old using the New Hope survey of the second year after baseline. The sample of children who were six years old or less by two years after baseline consists of 409 children out of the 904 children of female applicants with at least one child.

To evaluate if attrition compromised the randomization outcomes in the two experimental groups, Appendix B compares participant baseline characteristics across experimental groups. Table B.1 shows baseline characteristics of the original CFS sample. The majority of participants in the CFS are women (90%), more than half are African-American and 88% do not cohabitate with a spouse or partner. Moreover, only half of the sample has a high school diploma or GED certification and over 50% earned less than $10,000 in the last 12 months (1994 dollars). For all the variables in Table B.1, there are no statistically significant differences between treatment and control groups. When going from the CFS original to the estimation sample (only women), baseline characteristics do not exhibit economically significant changes and baseline characteristics remain balanced. Furthermore, baseline characteristics remained balanced in the sample of women with information on the SSRS variable, which exhibits considerable attrition (Table B.4).

4 Treatment effects

Bos et al. (1999) and Huston et al. (2001) presents estimated effects of New Hope on household behavior and child outcomes, for all children and their parents.[25] In this section, I estimate treatment effects on three household variables—income, labor supply, and child care—for the sample of women with young children.[26] I define "young" as a child that was four years of

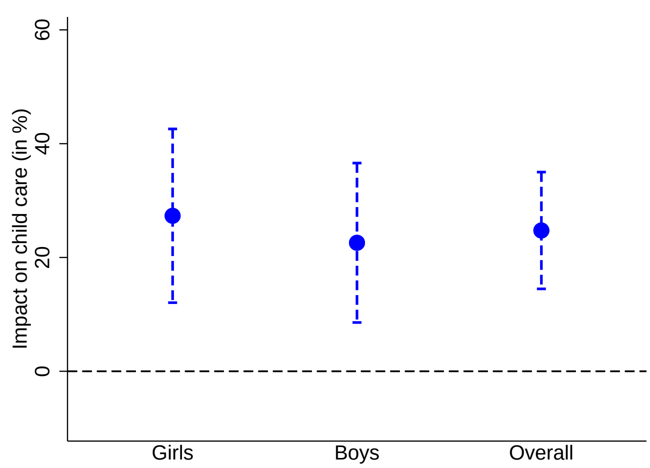
[25] See also Huston et al. (2003), Huston et al. (2005), Epps and Huston (2007), Miller et al. (2008), Grogger and Karoly (2009), and Huston et al. (2011).

[26] Later on, I define these three variables the main inputs in the production function of skills and thus are mediators the effects of New Hope on children. The estimated treatment effect of New Hope on the SSRS

age or less at the baseline year, thus, they were in their preschool years while New Hope ran. As I show next, treatment effects on household variables and child outcomes for this sample of adults and children are larger than the corresponding overall average effects.

Effects on parents' choices: labor supply, income, and child care use. Figure 3 shows treatment effects on child care use. The figure shows effects on the probability of using child care one year after baseline—thus, families were still under New Hope. The sample in this figure consists of children of women applicants who were less than four years of age at baseline ($N = 409$). I find that New Hope increased the likelihood of using center-based child care by 25 percentage points, from a baseline of 40. Estimated effects are similar across gender.

Figure 3: Treatment effects on child care probability



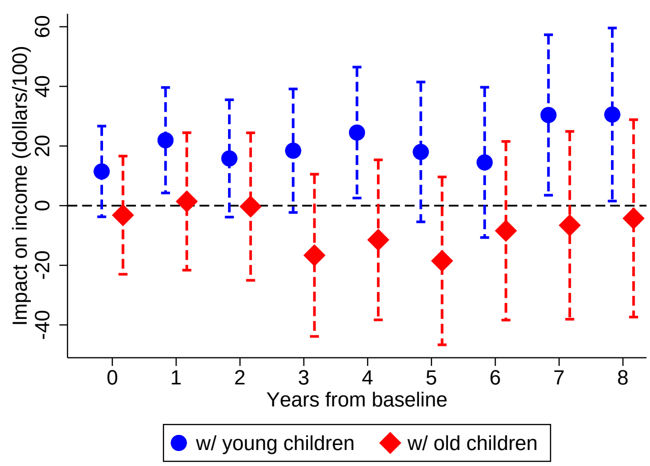
Notes: The figure plots treatment effects on child care use. The dependent variable equals 1 if the child used child care (Head Start, preschool, nursery school, or another child care other than someone's home) and as 0 if the child received home care (stayed at home with another family member or attended any other informal type of care). Dashed lines show 95% (robust) confidence intervals.

Figure 4 presents treatment effects on income. The income variable includes data on earnings, simulated EITC payments, and welfare cash transfers (see Section 3 for details). I show effects for two different samples: women whose youngest child was four years of age or less at baseline and women whose youngest child was older than four years of age. Even

variable for young children disappears when I control for income, labor supply, and child care. See Table 1 for the estimation of treatment effects on the SSRS without control variables.

though estimates are imprecise, the figure shows a clear difference in the treatment effects across these two sub-samples: treatment effects on income for families with young children are larger than those for families with relatively older children. For the first sub-sample and during the New Hope period, New Hope increased annual family income by $1,600$ dollars on average (a 13 increase from the baseline), with a statistically significant effect of $2,193$ dollars one year after baseline. Furthermore, treatment effects seem to have a constant effect in time, even after New Hope ended. In contrast, as I show below, treatment effects on child outcomes exhibit a clear fade-out pattern, implying that income cannot be the main mediator in explaining effects on child outcomes.

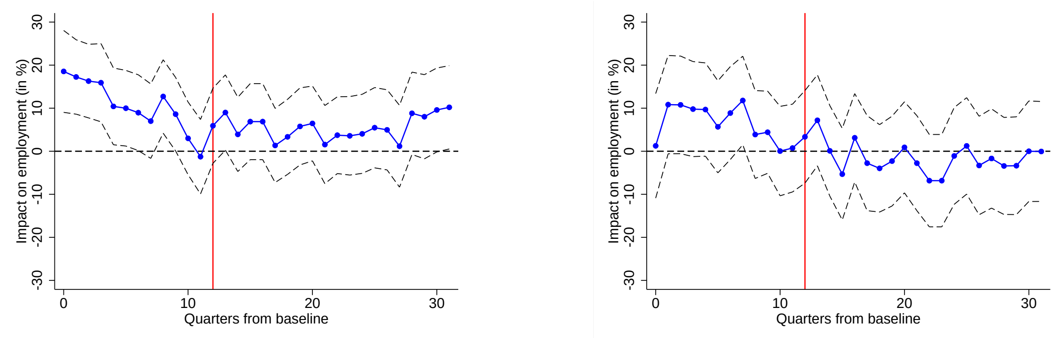
Figure 4: Treatment effects on income



Notes: The figure plots treatment effects on income. The dependent variable equals the sum of earnings, welfare payments, simulated EITC transfers, and New Hope cash paymentss. Dashed lines show 95% (robust) confidence intervals.

Figure 5 presents treatment effects on employment. The employment variable equals 1 if the individual shows a positive earnings record in a quarter and 0 otherwise. The baseline mean over the period I study equals 70%. Panel (a) shows effects for women with young children while panel (b) for women with older children. Results show larger labor-supply effects for the sample of women with young children. For this group and while New Hope ran, treatment effects average 8 percentage points from a baseline of 67%. Furthermore, treatment effects on employment are larger at the beginning of the New Hope period (up to 19 percentage points) and becoming statistically insignificant a few quarters before the end of the program, which is consistent with the fact that the New Hope treatment "intensity" decreased as the EITC schedule improved during the years.

Figure 5: Treatment effects on employment probability (in %)



(a) Age of youngest child ≤ 4 (b) Age of youngest child > 4

Notes: The figure plots treatment effects on quarterly employment probability. The dependent variable equals 1 if the individual reports a positive quartely wage and 0 otherwise. The left figure shows treatment effects for parents whose youngest child has less than or equal to four years of age at baseline. The right figure plots treatment effects for parents with older children. Dashed lines show 95% (robust) confidence intervals.

Effects on child outcomes Table 1 presents treatment effects on child outcomes. I estimate treatment effects using the SSRS variable expressed in standard deviations. Since sample size is much smaller in these regressions, I compute p-values using randomization-based inference, which are shown to be more robust to extreme outlier observations in small samples (Young, 2018). I estimate the effects of New Hope on the SSRS variable for the overall sample and stratifying by young and old children. Panels A, B and C present effects for two, five, and eight years after baseline. Column 1 presents treatment effects for the overall sample. For this sample, New Hope increased the measure of academic performance by 0.14 standard deviations, although the effect is not statistically significant. Columns 2 and 3 shows that the overall effect is explained by an increase of 0.46 standard deviations (statistically significant at the 5% level) for young children. The estimated effect for older children (0.04 standard deviations) is not statistically significant. Finally, estimated effects are statistically insignificant five and eight years after baseline.

Table 1: Treatment effects on academic achievement (in standard deviations)

	All (1)	Age ≤ 4 (2)	Age > 4 (3)
A. Two years after baseline			
Treatment	0.143	0.462	0.042
	[0.180]	[0.030]	[0.725]
Observations	377	92	285
B. Five years after baseline			
Treatment	0.033	-0.171	0.196
	[0.725]	[0.213]	[0.108]
Observations	476	219	257
B. Eight years after baseline			
Treatment	0.013	0.123	-0.098
	[0.897]	[0.357]	[0.448]
Observations	459	232	227

Notes: The table shows treatment effects of New Hope on the social skills rating system (academic sub-scale) expressed as standard deviations. I show the effects across sub-samples defined by age of child at baseline. Regressions with interacting terms include the gender dummy (1 for girl and 0 otherwise) as a control variable. In brackets, I show randomization inference-based p-values for the null hypothesis of null treatment effects.

5 Structural Model of Labor Supply, Child Care, and Child Human Capital

I have shown economically meaningful impact on household behavior and child academic performance of New Hope as a policy bundle. As in the case of New Hope, workfare reforms are usually implemented alongside others. Thus, identifying the effect of a particular policy without holding the other ones constant might bias reduced-form estimates (Chan, 2013; Blundell et al., 2016; Kleven, 2019). To understand the channels trough which the policy impacted child human capital and to assess the importance of the individual New Hope policies, I develop and estimate a dynamic model of household choices and child human capital. The model incorporates the economic constraints defined by various workfare programs. Individuals make labor supply and child care choices by taking into account this policy environment and the fact that these choices have effects on the accumulation of child human capital. In this way, the model allows for studying different sources that explain the reduced-form effects of workfare policies on child human capital.

The basic timing and features of the model are as follows. At the baseline year $t = 0$, a forward-looking agent receives the New Hope "shock" and draws an initial value of child human capital. Each period, the agent observes her household composition, a wage offer, and the current level of child human capital and makes labor supply (not working, part-time, or full-time work) and child care choices (center-based child care or home care) up until the child turns 18 years of age. These choices are shaped by various shocks to the agent's budget set—New Hope and the welfare system—and by a dynamic production function of child human capital. The forward-looking agent makes her choices trading off present and future associated benefits and costs of such choices; in particular, choices today affect the future accumulation of child human capital. Next, I present the model formally and explain its components in detail.

Utility function. The individual's current-period utility function corresponds to

$$U(c_t, h_t, \theta_t) = \ln(c_t) + \alpha_p \mathbf{1}\{h_t = 20\} + \alpha_f \mathbf{1}\{h_t = 40\} + \ln(\theta_t) \tag{1}$$

where h_t are weekly working hours. h_t takes three possible values: 0, 20 (part-time work), and 40 (full-time work). c_t represents monthly disposable income net of child care expenditures, expressed in per-capita units.[27] α^p and α^f capture the utility cost or benefit of part-time and full-time work. θ_t is child human capital, capturing teacher's subjective evaluation on the child performance in the classroom. η is the preference for the current stock of child human capital. The presence of θ_t in equation (1) implies that the individual makes her choices based on a weighted average of the stock of human capital across time.

Single and married individuals have the same utility function. For single agents, equation (1) represents the utility function of a parent that cares for her child's human capital.[28] For married individuals, I assume the principal caregiver of the child is the one who makes all

[27] t denotes a year in the individual life cycle. Nonetheless, monetary variables are expressed in monthly terms to capture the fact that the choice of part- versus full-time has consequences for eligibility to New Hope, which is defined in monthly terms. Thus, c_t can be interpreted as average monthly income of year t.

[28] Nearly 90% of participants are single or living alone with the child.

of the choices. Having a spouse affects choices by changes in consumption per-capita: more mouths to feed, another potential source of income, and changes in eligibility to and size of welfare payments.

Human capital production function. The technology of child human capital follows

$$\theta_{t+1} = \exp\left(\gamma_0 + \gamma_1(a_t) \times cc_t\right) \theta_t^{\gamma_2(a_t)} c_t^{\gamma_3(a_t)} \tau_t^{\gamma_4(a_t)}, \tag{2}$$

where cc_t equals 1 for center-based child care and 0 for home care (or any informal care at someone's home). τ_t are weekly hours the individual spends with the child. The constant in the production function (γ_0) is normalized so that $E[\ln \theta_t] = 0$ for $t > 0$. $\gamma_1(a_t)$ is a total factor productivity (TFP) parameter. It captures the human capital gain from center-based child care relative to home care, for a given (θ_t, c_t, τ_t). $\gamma_2(a_t)$ represents the influence of the current stock of human capital on the accumulation of future human capital—sometimes referred as "self-productivity" (Cunha and Heckman, 2006). $\gamma_3(a_t)$ is the effect of "money"—holding fixed labor supply and child care—and $\gamma_4(a_t)$ is the effect of parental time—holding fixed income and child care. The coefficients $\gamma_k(a_t)$, for $k = 1, \ldots, 4$, vary by age following

$$\gamma_k(a_t) = \gamma_k^y \mathbf{1}\{a_t \leq 5\} + \gamma_k^o \mathbf{1}\{a_t > 5\},$$

where γ_k^y and γ_k^o represent the coefficients of the production function for "young" and "old" children, for $k = 1, \ldots, 4$. I set $\gamma_k^o = 0$ for the coefficient associated with child care productivity ($k = 1$) as child care is not part of the choice set for old children.

Time with the child (τ_t) is determined by labor supply and child care choices. As children enter primary school, they cannot use child care services and the maximum possible time that parents and children can spend together is automatically reduced. Let $\overline{T}$ be the total available time the adult and a preschool child can spend together in a week and $\widetilde{T} < \overline{T}$ the time a school-age child spends at school. τ_t is defined as

$$\tau_t \equiv \begin{cases} cc_t(\overline{T} - 40) + (1 - cc_t)\left(\overline{T} - h_t\right) & \text{if } a_t \leq 5 \\ (\overline{T} - \widetilde{T}) - h_t & \text{otherwise.} \end{cases} \tag{3}$$

The logic behind equation (3) is as follows. If the child spends all week in home care ($cc_t = 0$), then labor supply determines how much time the adult spends with the child.[29] If $cc_t = 1$, then the child spends 40 hours a week outside the house being cared in a child care center. Hence, if $cc_t = 1$, then $\tau_t = \overline{T} - 40$ no matter how many hours the adult spends working. For school-age children, child care is not an option ($cc_t = 0$), but there is mandatory school. Hence, if $\overline{T} = 122$ (twenty four hours, seven days a week minus eight hours of sleep time) and $\widetilde{T} = 35$, available time for school-age children is $\overline{T} - \widetilde{T} = 77$ hours on a week.[30]

Equations (1), (2), and (3) determine the benefits and costs the agent faces when choosing labor supply and child care. First, child care allows the individual working more and thus having more income without reducing child human capital. Thus, she has more money to consume and produce further child human capital (if $\gamma_4(a_t) > 0$). In addition, if $\gamma_1(a_t) > 0$, child care has a direct and positive effect on child human capital. Hence, the benefits of child care are twofold: it directly produces child human capital and it lowers the marginal cost of labor supply.[31] Second, parental time with the child and leisure are indistinguishable. If the child is at home, any change in labor supply fully translates to impacts on child human capital given $\gamma_4(a_t) \neq 0$ (see equations 2 and 3).[32] Therefore, $\gamma_4(a_t)$ in the production function is a weighted average of the effects of active and passive time with the child. Furthermore, given her utility function (equation 1), the adult enjoys her leisure hours (dislikes her work hours) to the same degree regardless of whether or not the child is at a child care center or remains at home. Third, equations (1)-(3) imply that household choices can affect both directly and indirectly individual's welfare. Income enters individual's welfare directly each period and indirectly through θ_t.[33]

[29] There are three possible scenarios. If the individual does not work, then she spends all the available time with the child ($\tau_t = \overline{T}$). If she works part time, then she is 20 hours away from home in a week, so $\tau_t = \overline{T} - 20$. Analogously, $\tau_t = \overline{T} - 40$ if she works full time.

[30] For 2007-2008, the student's average number of hours per day in a school for Wisconsin is 6.9. See https://nces.ed.gov/surveys/sass/tables/sass0708_035_s1s.asp.

[31] Thus, and following (Del Boca et al., 2013), time with the child affects welfare only through changes in child human capital. However, changes in time with the child are followed by changes in labor supply, which does enter directly the utility function.

[32] Because New Hope data does not have time diaries, I cannot distinguish between passive or active time with the child in their different impacts of individual well-being (directly and indirectly through the production function of child human capital). Nonetheless, descriptive evidence shows that non-working mothers do spend more time with their children than working mothers (Guryan et al., 2008).

[33] We can interpret the indirect effect in two ways. First, part of what the agent purchases can also affect child human capital (e.g. books, food, etc). Second, having more money at home can relieve stress in the household, which can potentially enhance the parent-child relationship.

An additional child in the family does not directly impact current-value utility or the process of child human capital formation. Having more children influences choices only by shifting disposable income; an additional child in the household, all else equal, lowers c_t and changes the eligibility for and payments associated to welfare programs. For a family with more than one child, the adult makes her choices taking into account how they impact the human capital of a representative child.[34]

Wages. Each period, the individual draws a hourly wage offer, denoted by w_t. Following Bernal (2008), Chan (2013), and Del Boca et al. (2013), the offer depends on a vector of observable individual characteristics X_t^w. Furthermore, the wage offer is a function of an individual productivity that follows an AR(1) process. Formally, the wage offer process is given by

$$\begin{aligned} \ln w_t &= X_t^{w\prime} \beta^w + \nu_t^w, \\ \nu_t^w &= \rho \nu_{t-1}^w + \epsilon_t^w \\ \epsilon_t^w &\sim N(0, \sigma_w^2) \end{aligned} \tag{4}$$

where X_t^w includes a dummy variable for high school diploma, a constant, and a trend component. Its coefficients (which are constant in time) are known by the agent at the time she makes her choices.

For married applicants, spouse's labor market also affect time allocation decisions.[35] The individual draws an employment indicator, $\rho_t^E \in \{0, 1\}$, from a known binomial distribution, indicating whether the spouse is employed. If the spouse is employed, then he earns E_t, which comes from an exogenous process that follows

$$\ln E_t = X_t^E \beta^E + \nu_t^E, \tag{5}$$

[34] Household choices would differ from a multiple-children model—as Todd and Wolpin (2006) and Tartari (2015)—only in the case where there are young and old children at the same period in a given household (which occurs in 28% of the cases). Compared to such framework, average choices should not deviate as much (even though, at the individual level, choices would be different). Another option would be to disregard families with more than two children (Bernal, 2008; Del Boca et al., 2013), implying losing more than 50% of the sample.

[35] Thus, the model also features the insurance-child welfare tradeoff of Blundell et al. (2018).

where X_t^E includes a high school dummy and a constant and $\nu_t^E \sim N(0, \sigma_E^2)$.

Parental education and child human capital are related via individual choices. The level of parental education is an input in the wage process, which in turn affects labor supply and child care choices. Because human capital is affected by income, time, and child care, parental education has an indirect effect on child human capital.

Disposable income. The budget set incorporates various features of the welfare system. Income is a function of labor supply, earned income, and various workfare programs. Eligibility to these programs and payment amounts depend on working hours, earned income, and family composition.

Disposable income is the sum of earnings and cash from welfare programs. Let k_t and m_t be the number of children and a marriage indicator (1 if the household has two adults married to each other or living together and 0 otherwise). Income (I_t) is given by

$$\begin{aligned} I_t = {} & w_t h_t \times 52 + EITC_t(w_t, h_t, k_t, m_t) + NH_t(w_t, h_t, k_t, m_t) \\ & + B_t + S_t. \end{aligned} \tag{6}$$

In the equation above, $EITC_t(.)$ corresponds to EITC payments. If the individual is eligible to receive these payments, she always comply.[36] The same happens with the New Hope payments, $NH_t(.)$. B_t and $SNAP_t$ are cash transfers from AFDC (or TANF) and Food Stamps (now known as SNAP). As with New Hope and the EITC, and following (Blundell et al., 2016) for the UK context, the individual always takes up the benefits of welfare programs (AFDC and SNAP) conditional on eligibility.[37] However, she faces random i.i.d. take-up shocks, which capture misinformation about the welfare system. Specifically, at the beginning of each period, the individual draws two values, $\rho_t^B, \rho_t^S \in \{0, 1\}$, from a pair

[36] The EITC national take-up rate is estimated at over 80% (Scholz, 1994; Plueger, 2009; Hoynes and Rothstein, 2016). Furthermore, New Hope representatives took care to advise participants about how to take advantage of the EITC (Bos et al., 1999). As for New Hope, assuming eligibility on an annual basis and using the definitions of hours worked and gross income that is consistent with the data for estimating the structural model, I estimate a take-up rate of 92%.

[37] An alternative structural framework would allow individuals to choose whether they want to take up the benefits and include taste parameters ("welfare stigma" coefficients) associated with each program. However, I do not have enough sources of exogenous variation to identify stigma coefficients (Keane and Moffitt, 1998; Chan, 2013). Appendix D (figures D.1 and D.2) shows that take-up rates (conditional on eligibility) for the AFDC and Food Stamps do not follow an obvious pattern across income quantiles.

of known, time-invariant binomial distributions, indicating whether the individual takes up the corresponding payment or not. These information shocks affect only AFDC and Food Stamps. The available money from AFDC and Food Stamps follows:

$$B_t \equiv \rho_t^B B_t^*(w_t, h_t, k_t, m_t),$$
$$S_t \equiv \rho_t^S S_t^*(w_t, h_t, k_t, m_t),$$

where $B_t^*(.)$ and $S_t^*(.)$ are potential AFDC and Food Stamp payments.

Each of the payment functions $EITC_t(.)$, $NH_t(.)$, $B_t^*(.)$, and $S_t^*(.)$ are given by precise formulas determining eligibility and payment levels. They are a time-varying function of the level of earnings, labor supply, and family composition (k_t and m_t).[38] Families have perfect information regarding the evolution of rules of the welfare system; the uncertainty faced in this context is in future misinformation shocks about AFDC and Food Stamps.[39] Finally, eligibility rules are always enforced, including the New Hope work requirement.[40]

During the time frame of the model, AFDC is replaced by TANF. For this sample, the State of Wisconsin implemented the Wisconsin Works program (W-2), which eliminated AFDC's unconditional cash transfers and established time limits for welfare utilization. Specifically, W-2 offered paid community service jobs at a flat rate. So from 1997 onward ($t = 2$), I assume that the wage of the state-provided CSJ is part of the pool of potential log-wage offers (equation 4). In the model, individuals do not face time limits for W-2.[41]

The cost of child care services depend on whether or not the individual is the treatment group and the probability of receiving a free child care spot. The individual can use free child care services, but slots in the market are limited. Every period, the individual draws a value $\rho_t^c \in \{0, 1\}$ (estimated alongside other structural parameters) indicating if the individual has s free child care slot. If she does, she can use child care for free only if earnings are below a certain threshold E^*. If she does not have the option of free child care, the parent can pay for child care services at a known and fixed price p. If the agent is in the New Hope treatment

[38] See Appendix D for details.

[39] In the case of New Hope, the program's representatives explained the details of the benefits package to all participants. Furthermore, representatives were available throughout the eligibility period to answer any questions participants might have had (Brock et al., 1997).

[40] New Hope agents implemented various procedures to ensure that requirements were met. See Section 2.

[41] I do not include time limits since I do not have data on labor supply and welfare use beyond 2003.

group and works full time, she gets a lower copayment, $\underline{p} \leq p$, which depends on the level of earnings (see Section 2). Any type of informal child care arrangement that might happen in practice when the parent is not at home and the child is not at a center-based child care has zero cost (or, alternatively, p can be interpreted as the relative cost of formal versus informal child care). Formally, let $\delta(\rho^c_t, w_t, h_t, D)$ be the child care cost function, given by:

$$\delta(\rho^c_t, w_t, h_t, D) = \begin{cases} 0 & \text{if } \rho^c_t = 1 \text{ and } w_t h_t < E^* \\ \delta^* & \text{otherwise,} \end{cases} \tag{7}$$

where

$$\delta^* \equiv (1-D)p + D\left[\mathbf{1}\{h_t = 40\}\underline{p}(w_t, h_t) + (1 - \mathbf{1}\{h_t = 40\})\, p\right]. \tag{8}$$

Finally, the individual cannot save or borrow.[42] The individual receives utility from per-capita income net of child care expenditures. Thus, c_t is given by

$$c_t = \frac{I_t - cc_t \times \delta(\rho^c_t, w_t, h_t, D)}{1 + m_t + k_t}. \tag{9}$$

Family composition. Marriage formation and childbearing are exogenous processes. Each period, the individual draws a marital status (1 if married and 0 if single) and childbearing values (1 if there is a new child in the family and 0 otherwise) from known binomial distributions with probability parameters m^*_t and k^*_t. These probabilities depend on observed participant characteristics and past family composition, as follows:

$$m^*_{t+1} = f_m(X^m_t, m_t), \tag{10}$$

$$k^*_{t+1} = f_k(X^k_t, k_t, m_t), \tag{11}$$

where m_t equals 1 if the participant is married or living with her partner and 0 otherwise, and k_t indicates the number of children in the household. X^m_t includes a constant and age of the adult. X^k_t includes a constant, age, and age squared of the adult.

[42] There is no evidence suugesting that individuals were fully able to save for future consumption. In the control group, from the year-five interview, 58% declared some concern about not having enough money to buy food. Additionally, a large share does not access to banking services, 42% of individuals do not have a checking account, and 52% do not have a savings account.

The dynamic problem. In each period, given a set of state variables, the individual solves a dynamic problem. The state variables of this problem are grouped in the vector $\boldsymbol{s}_t = (D, m_t, k_t, a_t, \theta_t, \boldsymbol{X}, \nu_t^w, \boldsymbol{\rho}_t, p)$, where $\boldsymbol{X} \equiv \left(X^w, X^m, X^k\right)$ contains the wage offer, marriage, and childbearing processes control variables and $\boldsymbol{\rho}_t \equiv \left(\rho_t^E, \rho_t^B, \rho_t^S, \rho_t^C\right)$ the spousal employment indicator, misinformation shocks to welfare take-up and the free child care slot indicator. For a given $\boldsymbol{s}_t$, each period the agent maximizes the present discounted value of the utility stream by choosing labor supply and child care type. Let $\mathcal{C} = \{0, 1\}$ and $\mathcal{H} = \{0, 20, 40\}$ be the choice sets of child care and labor supply. We can represent the entire choice set, for any period, as $\mathcal{J}(a_t) = \mathcal{C} \times \mathcal{H}$ if the child is young ($a_t \leq 5$) and $\mathcal{J}(a_t) = \mathcal{H}$ otherwise ($a_t > 5$). Given that agents differ in their children's age, each individual solves a problem of a different time horizon. Let $T(a_0) \equiv 18 - a_0$ be the terminal period for an individual with a a_0-year-old child. Thus, for a one-year-old child arriving in period $t = 0$, the parent solves the dynamic problem for 17 years after baseline, stopping when the child turns 18 of age.

Let $u(\boldsymbol{s}_t, j)$ be the current-period utility for a given state $\boldsymbol{s}_t$ and choice $j \in \mathcal{J}(a_t)$. For any t, the problem of the forward-looking individual is given by

$$
\begin{aligned}
V_t(\boldsymbol{s}_t) &= \max_{j \in \mathcal{J}(a_t)} \{V_t^j(\boldsymbol{s}_t)\} \quad \text{subject to (1)-(11)}, \\
V_t^j(\boldsymbol{s}_t) &= u(\boldsymbol{s}_t, j) + \beta E[V_{t+1}(\boldsymbol{s}_{t+1}) \mid \boldsymbol{s}_t, j] \qquad t < T(a_0),
\end{aligned} \tag{12}
$$

where the expected value operator is taken with respect to all of the unobservables in the model.

The model is closed with initial and terminal conditions. At baseline ($t = 0$), the agent knows her associated fixed values defining family composition (m_0, k_0), child age (a_0), observed characteristics $\boldsymbol{X}$, and the random assignment indicator D. Additionally, the individual draws an initial value for child human capital θ_0, which is related to the parent's unobserved characteristics. In particular, the initial shocks to unobserved productivity and child human capital, ε_0^θ and ε_0^w, follow a joint normal distribution with correlation coefficient ρ_θ. In the final period, the individual can no longer invest in child human capital. The associated terminal value function is thus

$$V^j_{T(a_0)}(\boldsymbol{s}_{T(a_0)}) = \max_{j \in \mathcal{J}_{T(a_0)}} \left\{ \tilde{u}(\boldsymbol{s}_{T(a_0)}, j) \right\} + \eta \ln \theta_{T(a_0)}.$$

6 Identification and Estimation

6.1 Identification

The policy environment within the model offers various sources of exogenous variation that can be exploited for identification. First, around the New Hope period, major changes were to the welfare system were implemented. In particular, the model considers the end of the AFDC and replacement by the TANF, expansions to the EITC schedule, and the implementation of the large-scale child care subsidy funded by the CCDF. Second, changes in these welfare payments across time have been substantially different across different families structures, which is a source of exogenous variation that has been commonly used in the literature (Eissa and Hoynes, 2004; Meyer and Rosenbaum, 2001; Dahl and Lochner, 2012). Finally, there are several discontinuity points in the rules of the different mean-tested programs, generating natural experiments at the local level. All of these policy shocks shape labor supply and child care decisions without directly changing preferences, the wage offer equation, or the production function. Therefore, identification hinges on the comparison of choices and outcomes across periods (before and after policies are implemented), family composition, and at different points of the wage offer distribution for a given set of parameters determining preferences, wages, and child outcomes.[43]

6.2 Estimation

To keep estimation computationally feasible, I follow Gourinchas and Parker (2002), De Nardi et al. (2010), Voena (2015), and Blundell et al. (2016) and proceed in two steps. In the first step, I estimate the parameters of some of the exogenous processes straight from the data. In the second step, I estimate the rest of the structural models using the simulated method

[43] In Appendix **??**, I estimate the wage offer equation using a control function approach. To this end, I use the model-predicted propensity score to account for non-random selection into work in the log wage equation—hence, I implicitly use all of the sources of variation discussed above as exclusion restrictions. The results show that structural and control-function estimates are quantitatively similar.

of moments. I use moments that meet the single-crossing property of the previous section directly in the estimation procedure. I explain the exact procedure next.

External estimation and calibration. Table 2 summarizes the sources for external estimation an calibration. To obtain the parameters governing the probability of being married (m^*_{t+1}) and of childbearing (k^*_{t+1}), I assume linear functions for these processes (equations 10 and 11) and estimate a linear probability model of m_{t+1} on m_{t-1} and X^m_{t-1}. I then use the resulting reduced-form parameters to identify the marriage and childbearing linear processes and predict the parameters of the binomial distribution determining the probabilities of marriage and childbearing.

I determine the rest of the parameters of the exogenous processes to match different observed statistics. To calibrate the monthly child care market price, I take the value reported in Bos et al. (1999) corresponding to the average sum of individual copayments ($751 a month). I define the probability of receiving AFDC and Food Stamps—conditional on being eligible—as the average take-up observed in the data (60% and 70%, respectively). Finally, I follow Chan (2013) and set the discount factor to $\beta = 0.86$, which is a middle point between the equivalent parameters of Swann (2005) and Keane and Wolpin (2010).

Table 2: Calibrated and externally estimated parameters

Parameter/equation	**Source for estimation/calibration**	**Values**
Probability of being married	OLS: m_{t+1} on m_{t-1} and X^m	$m^*_{t+1} = 0.21 - 0.002age + 0.8m_t$.
Probability of childbearing	OLS: $(k_{t+1} - k_t)$ on m_{t-1}, k_{t-1} and X^k	$k^*_{t+1} = -0.11 + 0.05age -$ $+0.0003age^2 - 0.006k_t - 0.1m_t$
Child care price	Bos et al. (1999)	$751 monthly
Take-up probabilities of AFDC and SNAP	Average AFDC and SNAP take-up conditional on eligibility	0.6 and 0.7
Discount factor (β)	Chan (2013)	0.86

Notes: The table describes the sources for estimation or calibration of the structural parameters determined outside the estimation procedure.

Internal estimation. In a second step, I use the simulated method of moments to estimate the rest of the parameters. The procedure matches the estimated moments of an auxiliary model using observed data with equivalent estimates from the model-simulated data (Gourieroux et al., 1993).

The estimation problem can be stated as follows. Let $\hat{g}$ be the vector of moments extracted from the data. I solve the model $M = 10$ times for a sample size of $n = 904$ children and compute the required moments from simulated data.[44] Let $\{\boldsymbol{\epsilon}_t^m\}_{m=1}^M$ denote the structural random shocks (fixed across the estimation procedure). Let ψ be the vector of structural parameters of the model. Define $\{y_{it}^m(\psi)\}_{m=1}^M$ as the simulated choices associated with the M draws of structural random shocks. Let $\hat{g}^m(\psi)$ be the equivalent moment associated with the m draw. I estimate the structural parameters ψ by solving

$$\hat{\psi} = \arg\min_{\psi \in \Psi} [\hat{g} - \hat{g}(\psi)]' W [\hat{g} - \hat{g}(\psi)],$$

where $\hat{g}(\psi) = \frac{1}{M} \sum_{m=1}^M \hat{g}^m(\psi)$ and $\widehat{g}$ is the vector of auxiliary estimates from the data.

Following Del Boca et al. (2013) and Blundell et al. (2016), I define W as the inverse of the diagonal of the estimated variance-covariance matrix of $\hat{g}$. I do not use the efficient weighting matrix because of its poor small-sample properties (Altonji and Segal, 1996). Finally, I use the bootstrap (500 samples) to estimate W and compute standard errors using the asymptotic formula given by Gourieroux et al. (1993).

Target moments. Estimation exploits a set of unconditional and conditional moments. The matched moments are non-experimental, while experimental moments are left for validation. To estimate preferences for hours of work and child human capital, I use the labor supply and child care choices of children's parents. To estimate the production function process, I use the correlation of consumption and parental time with the child (as defined in equation 3) with the SRS assessment. To estimate the measurement system, I include first and second moments of the sample distribution of SSRS. Finally, to estimate the wage offer and spousal income processes, the auxiliary model includes the OLS coefficients of the corre-

[44] I use backward induction to solve the model and obtain paths of simulated choices. I compute $V_t(\boldsymbol{s}_t)$ for a grid of the state space and then use linear interpolation (in which I include polynomial terms of the state variables) to approximate $V_t(\boldsymbol{s}_t)$ for values outside the grid (Keane and Wolpin, 1994; Keane et al., 2011). I set the grid size (500 points) and the number of draws for the Monte Carlo integration (25 draws) to balance precision and computational time.

sponding sample regressions in the context of equations (4) and 5.[45] Appendix E describes how I construct the main variables of the model combining administrative and survey data to compute target moments for estimation. Appendix E shows that the model successfully matches all target moments.

7 Model Estimates and Validation with Experimental Data

7.1 Estimated Structural Parameters

Table 3 presents the estimated structural parameters. For estimation purposes, the baseline sample consists of the CFS sample of children. After removing observations with missing data on household information, estimation uses data on 904 children and of their principal caregivers. Overall, although there are notable exceptions, estimated coefficients are somewhat similar to what we can find in the literature.

Panel A presents the parameters of the utility function (equation 1). Child human capital is positively valued by the agent: without considering the long-term effects on the human capital stock, the structural estimates imply that the individual is willing to sacrifice 0.9 (log) consumption units for an increase of one (log) unit of child human capital. This number falls in the wide range of similar estimates found in the literature: while Bernal (2008) estimates a null coefficient, Del Boca et al. (2013) documents that a one-percent increase in child human capital is more valued than the same increase in consumption. The necessary changes in log consumption to work part- or full-time work and keep instant utility constant (-0.83 and -0.14) are larger than those found by Blundell et al. (2016) for a similar demographic group.

Panels B and C show the estimated parameters of the wage offer process of the woman and the earnings process of her spouse (equations 4 and 5). In the case of the woman, I find that the wage offer increases for everyone—capturing a growing labor demand—given a positive coefficient associated with the time trend.[46] A high school diploma increases the wage offer of the woman and spouse by 22% and 15%, values that are similar to those found in the

[45] The auxiliary wage regression uses data only for individuals with non-zero wages. Also, moments using child test scores use less observations given that they are observed only for children of age five and above. See Section 3 for details.

[46] Employment probability for both treatment and control groups grows throughout the covered period 1994-2003. See Miller et al. (2008) and Section 2.

literature. For women, Blundell et al. (2016) report that a high school graduation increases wages by 20% while for men, Heckman et al. (2016) documents a 10% wage return to high school graduation. The variance of the error term of the mother's wage process (0.26) is bigger and the autocorrelation coefficient of the unobserved component of the wage offer (0.57) is lower compared to what Blundell et al. (2016) find for women with secondary and high school education. Hence, relative to the Blundell et al. sample, New Hope participants face a larger degree of uncertainty regarding future wage shocks. In contrast, spouse's earnings process is much less uncertain, with a variance that is five times smaller that that of the woman.

Table 3: Estimated structural parameters

Parameter	Estimate	S.E.
A. Utility function		
Part-time disutility	-0.137	0.006
Full-time disutility	-0.830	0.032
Preference for human capital	0.916	0.107
B. Wage offer		
High school dummy	0.219	0.017
Trend	0.081	0.002
Constant	1.535	0.004
Variance of error term	0.264	0.008
AR(1) error term	0.573	0.021
C. Spouse income		
High school dummy	0.154	0.005
Constant	7.217	0.003
SD of error term	0.227	0.002
Employment probability	0.919	0.003
D. Production function and child care		
Child care TFP (young)	0.362	0.018
Lagged human capital (young)	0.889	0.008
Income (young)	0.083	0.005
Time (young)	-0.000	0.015
Lagged human capital (old)	0.797	0.008
Income (old)	0.009	0.005
Time (old)	0.009	0.015
SD of shock to human capital	0.502	0.037
Correlation of wage and initial human capital	-0.001	0.005
Probability of free child care	0.428	0.025

Notes: This table shows the estimated parameters of the model presented in Section 5. The utility function follows $U(c_t, h_t^p, h_t^f, \theta_t) = \log c_t + \alpha^p h_t^p + \alpha^p h_t^f + \eta\theta_t$. The wage offer obeys $\ln w_t = X_t^{w'} \beta^w + \epsilon_t^w$, where X_t^w includes a constant, age, age squared, a dummy for high school diploma and $\epsilon_t^w \sim N(0, \sigma_w^2)$. The production function is given by $\theta_{t+1} = \exp\left(\gamma_0 + \gamma_1 cc_t \mathbf{1}\{a_t \leq 6\}\right) \theta_t^{\gamma_2} c_t^{\gamma_3} \tau_t^{\gamma_4}$.

I show the estimated parameters of the production function and measurement system in

Panel D. For young children, net per-capita earnings has a positive effect on human capital. Assuming no behavioral responses and holding labor supply constant, a 1,000-dollar boost in one period rises child human capital by 13% of a standard deviation for young children and by 1% for older children. A middle point of these two estimates coincides with those reported by Dahl and Lochner (2012) and Agostinelli and Sorrenti (2018).[47] On the other hand, the age profile of the effect of money on child outcomes does not follow a clear trend in the literature; while Del Boca et al. (2013) find increasing skills returns to material investment, Del Boca et al. (2019) and Agostinelli and Wiswall (2016) find the opposite. Time at home has a negligible effect on children's human capital, both for young and old children. This result is in contrast with studies showing economically meaningful impacts of parental time on child outcomes (Cunha et al., 2010; Del Boca et al., 2013; Attanasio et al., 2015). What might explain this difference is that my sample is not representative of the average, and that low-income households could have lower productivity of time inputs. Child care has a sizable effect on child human capital. My estimates imply that choosing child care instead of home care (assuming the caregiver is working full time) increases child skills by 35% of a standard deviation. Quantitatively similar effects of child care on participant children have been also found in the Head Start literature (Feller et al., 2016; Kline and Walters, 2016). Finally, the human capital production function contains substantial persistence. The relatively high persistence in the production function is a consistent finding in the literature (Cunha and Heckman, 2006; Cunha et al., 2010; Attanasio et al., 2015). A strong persistence component implies that any shock to the human capital process at early ages has nearly permanent consequences for skills production in the future.

7.2 Validation using Experimental-Based Treatment Effects

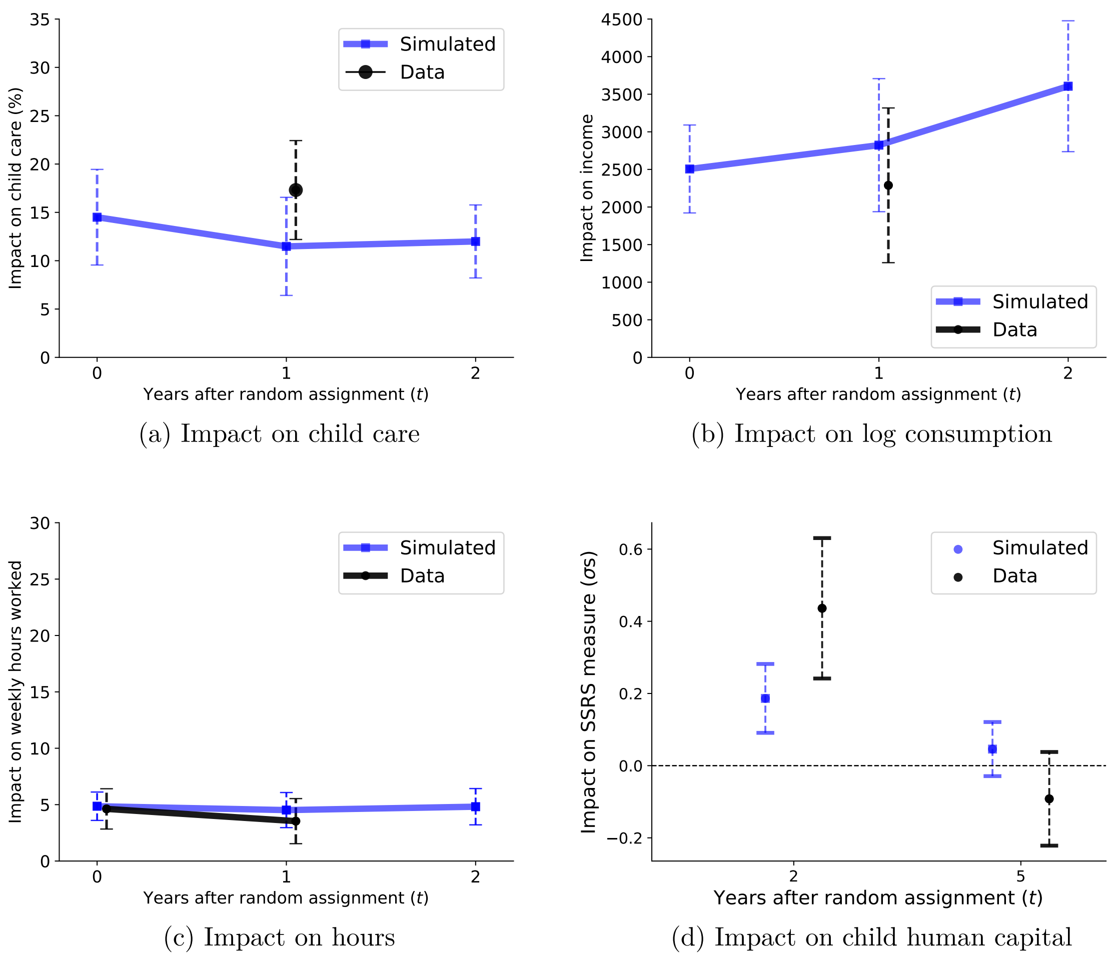
Before presenting the counterfactual experiments, I analyze the model's capacity to predict non-targeted moments. These moments—which were not used in estimation—exploit the experimental variation induced by the New Hope random assignment. This form of validation has not beed used in the structural literature on child outcomes and household behavior

[47] Bernal (2008) and Del Boca et al. (2013) also find that money has a moderate effect on child cognitive skills.

(Bernal, 2008; Del Boca et al., 2013; Mullins, 2019; Chaparro et al., 2020).

Figure 6 compares simulated and "observed" treatment effects of New Hope on key variables. Panels (a)-(c), compare the model-generated impact of New Hope on child care, consumption, and hours worked with the estimated effects from the experimental data, for the sample with children under six years of age by $t = 2$. The figures suggest that the model has good predictive performance with respect to treatment effects on inputs of the child human capital process. Panel d) compares simulated and data-based treatment effects on the observed human capital measure (SSRS). Although the peak of the effects is lower in the simulated estimate (0.2σ versus 0.4σ), the model matches the initially increasing and then fading-out pattern of the human capital effects of New Hope.

Figure 6: Simulated and observed treatment effects



(a) Impact on child care

(b) Impact on log consumption

(c) Impact on hours

(d) Impact on child human capital

Notes: Panels (a)-(c) compare the simulated and observed treatment effects on household variables. Panel (d) depicts the simulated impact on the observed measure of academic achievement (SSRS).

8 Understanding the Effects of New Hope

Having showed that the model has good predictive power in key counterfactual exercises, I now turn to analyze the channels that account for the effects of the program on children. I divide the analysis in two. First, I show which policies can account for the effects of New Hope on children. Second, I study the influence of household-level variables in the human capital effects of New Hope on children.

8.1 Unpacking New Hope: Policy-Level Mechanisms

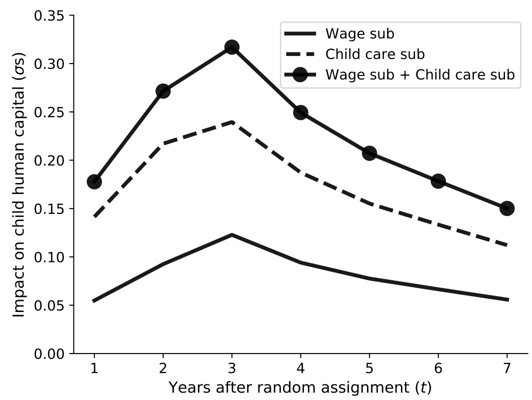
I have shown that New Hope, as a policy package, had economically meaningful effects on families. In this section, I study which components in the New Hope policy bundle were more influential in changing parental behavior and child outcomes. To do so, I simulate different versions of New Hope and analyze their effects on labor supply, child care use, income, and child human capital I start by evaluating the effect that income and child care subsidies have on child human capital and then continue to analyze the role played by the full-time work requirement.

I compute the effects of different New Hope policies on children and the family. In these experiments, I change the parameters of the New Hope package and re-compute treatment effects on household behavior and child outcomes under different versions of New Hope. As with previous analyses, I focus on the sample of children who were six years of age by two years after baseline.

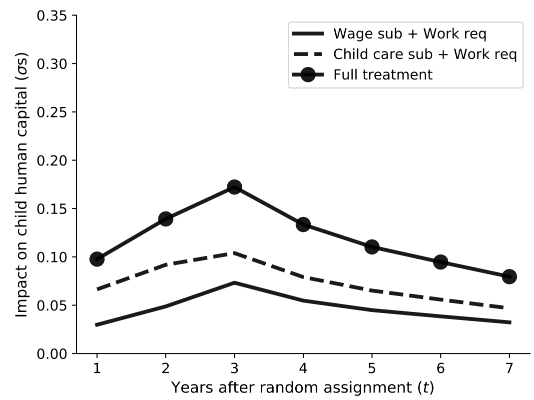
Figure 7 (panel a) presents the effect of different policy bundles on child human capital. I simulate the effects of three different versions of New Hope: one that includes only a wage subsidy, one that only has a child care subsidy, and another with these two policies combined. For now, I assume that each of these policies do not consider a full-time work requirement. The figure shows increasing then decreasing treatment effects on child human capital. All three policies reach a treatment-effect peak at three years after baseline. The wage subsidy experiment—given that the counterfactual policy is the actual EITC,—might be considered as the estimated effect of an EITC expansion, much like the ones that were implemented in the 90s. The effect on child human capital of this EITC expansion equals 0.09σ on average.

For all periods, the effect of the child care subsidy on child human capital is larger than that of the wage subsidy: on average, the effect is is 0.09σ bigger. Therefore, the child care subsidy component of New Hope is producing most of the effects of the policy bundle on child human capital.

Figure 7: Effects of New Hope policies on child human capital



(a) Without work requirement



(b) With work requirement

Notes: The figure plots the impact of various combinations of New Hope policies on child human capital. The sample consists of children who were six years of age or less by $t = 2$ years after baseline.

The fact that the New Hope had a series of policies combined gives us the opportunity to study how policies might complement (or substitute) in producing child human capital. Because of complementarities at the policy and production-function level, the effect policies in isolation might not be equal to the effects of combined policies. However, most of the literature evaluating welfare reforms does not consider this possibility (Moffitt, 2003, 2016). Figure 7 presents evidence on this front. I find that effect on child human capital of a child care subsidy depends on which policies are implemented in the first place. Consider the effect of a child care subsidy when a wage subsidy was already in place. On average, such policy increases human capital by 0.14σ. Implementing the child care subsidy when no policy is in place boosts child human capital by 0.17 standard deviations. Thus, these two policies are substitutes, in the sense that one particular policy reduces the human capital return to the other policy.[48]

Now consider the effects of a work requirement. Many welfare experiments—similar to

[48]See Almond et al. (2018) for further examples of how policies or events affecting child human capital can be reinforced (or dampened) by subsequent human capital shocks.

New Hop—have incorporated work requirements (Grogger and Karoly, 2009). However, reaching a definite conclusion have proven to be difficult as the impact of the work requirement has not been experimentally tested in isolation. Figure 7 (panel b) presents novel evidence regarding the effects of the work requirement. It plots the effects of different policy combinations on child human capital, where all of these policies include a work requirement. Compared to policies without work requirements (Figure 7), the effects on child human of policies with the work requirement capital are lower. Requiring full-time work cuts the effect of the child care and wage subsidies by half: combined with the work requirement, the child care and wage subsidies increase child human capital by 0.07σ and 0.05σ, respectively. Taking both policies together, if New Hope had not included a work requirement, the impact on child human capital would have been 0.1σ bigger. Overall, the New Hope work requirement caused a negative effect on child human capital.

To sum up, the above results are in line with current research on the effects of child care subsidies on the family (Baker et al., 2008; Herbst and Tekin, 2010, 2016; Havnes and Mogstad, 2011, 2015; Black et al., 2014; Cornelissen et al., 2018). A common result of recent studies is that the impact of child care subsidies on children from low-income families is larger than on the average family (Havnes and Mogstad, 2015; Cornelissen et al., 2018). My counterfactual analysis indicates that once low-income families have access to affordable child care, average effects of workfare policies on children can emulate economically meaningful effects that are found for high-quality specific early childhood interventions (Gross et al., 1997; Campbell et al., 2002; Heckman et al., 2010; Gertler et al., 2014) and larger-scale programs such as Head Start (Kline and Walters, 2016; Feller et al., 2016).

8.2 Mediation Analysis: Household-Level Mechanisms

To evaluate the relative importance of inputs in the production function, I analyze their mediating influence in accounting for the impact on New Hope on children. So far, I have shown that New Hope induced participants to work more; this effect, by itself—holding the rest of inputs constants—has a negative albeit small effect on child human capital. However, by working more individuals have more income, which has a positive effect on child human capital. Further, the program also increased the use of child care, increasing child human capital. Next, I provide a quantitative analysis on each of these channels.[49]

Consider the following representation of the academic achievement production function:

$$\theta_{t+1}^d = f(\theta_t^d, \tau_t^d, cc_t^d, c_t^d)$$

where $d \in \{0,1\}$ indicates assignment to an experimental group and z_t^d the value of z_t under the counterfactual scenario that the individual belongs to experimental group d. The individual-level treatment effect of the program corresponds to $\ln\theta_{t+1}^1 - \ln\theta_{t+1}^0 = f(\theta_t^1, \tau_t^1, cc_t^1, c_t^1) - f(\theta_t^0, \tau_t^0, cc_t^0, c_t^0)$. This term can be decomposed as

$$\begin{aligned}
\ln\theta_{t+1}^1 - \ln\theta_{t+1}^0 &= \underbrace{[f(\theta_t^1, \tau_t^1, cc_t^1, c_t^1) - f(\theta_t^1, \tau_t^1, cc_t^1, c_t^0)]}_{\text{explained by consumption}} \\
&+ \underbrace{[f(\theta_t^1, \tau_t^1, cc_t^1, c_t^0) - f(\theta_t^1, \tau_t^1, cc_t^0, c_t^0)]}_{\text{explained by child care}} \\
&+ \underbrace{[f(\theta_t^1, \tau_t^1, cc_t^0, c_t^0) - f(\theta_t^1, \tau_t^0, cc_t^0, c_t^0)]}_{\text{explained by time}} \\
&+ \underbrace{[f(\theta_t^1, \tau_t^0, cc_t^0, c_t^0) - f(\theta_t^0, \tau_t^0, cc_t^0, c_t^0)]}_{\text{explained by self-productivity}} \qquad (13)
\end{aligned}$$

where each term on the right-hand side identifies the contribution of the corresponding input in explaining the effect of the program.[50]

Table 4 presents treatment effects on household variables of different types of policies. In each row, the table depicts the effect of a particular policy (in columns) on average labor supply, child care use, and per-capita disposable income up to two years after baseline. To compare these results to the related literature, I emphasize effects on the extensive margin of labor supply. The wage subsidy has larger effects on income and employment than the child care subsidy: the wage subsidy increases employment and consumption by 9 percentage points and 559 dollars, while the child care subsidy has substantially smaller (and negative in the case of employment) effects on both variables. In contrast, the impact on child care use is bigger for the child care subsidy (24 percentage points) than for the wage subsidy (5

[49] With the exception of Epps and Huston (2007), previous literature does not have a formal analysis of the mediating factors that lead to the observed impacts on child outcomes. See Huston et al. (2001, 2005, 2011).

[50] Given the linearity of $f(.)$ (see equation 2), the order of the terms in equation (13) does not affect the estimate of the contribution of each input.

percentage points). The labor supply effects of wage subsidies are similar to the ones from the literature exploiting quasi-experimental variation (Hoynes and Patel, 2020). On the other hand, the slightly negative effects of the child care subsidy on employment might be due to income effect: for parents who use child care without the policy, the subsidy represents a sizable income effect. Nevertheless, the order of magnitude and sign of the simulated effect is consistent with a large literature. See Enchautegui et al. (2016) and the reviews by Blau (2003) and Morrissey (2017).

The table also shows the effects of policies with a full-time work requirement. Introducing the requirement in the wage and child care subsidies increases the labor supply effects of both policies, although such increment is small (about one hour of work a week).[51] Furthermore, requiring full-time work reduces their effects on child care use of these two subsidies. Taking both policies together, if New Hope had not consider the work requirement, the effects on child care use would have been almost twice as big while effects on labor supply would have been close to zero. What explains such reduction in the effects on child care use? For some individuals, as working full time is costly, the work requirement makes the wage and child care subsidies less attractive. For those parents, the increased income and gain on child human capital of taking up both subsidies does not compensate the cost of working full time.

Table 4: Simulated effects of income and child care subsidies on household-level variables

ATE	(1)	(2)	(3)	(4)	(5)	(6)
Income (US$)	559	815	332	155	262	690
Employment	0.087	0.067	0.037	-0.019	0.021	0.057
Child care	0.052	0.248	0.033	0.243	0.085	0.111
Wage subsidy	✓	✓	✓			✓
Child care subsidy		✓		✓	✓	✓
Work requirement			✓		✓	✓

Notes: The table shows the impact of New Hope on consumption, part-time work, full-time work, and child care. The sample corresponds to children who are six years of age or less by $t = 2$. All simulated effects are averages of annual effects from the baseline period to two years after baseline. Each policy mix (indicated with "✓") is compared to a counterfactual scenario where no policy is implemented.

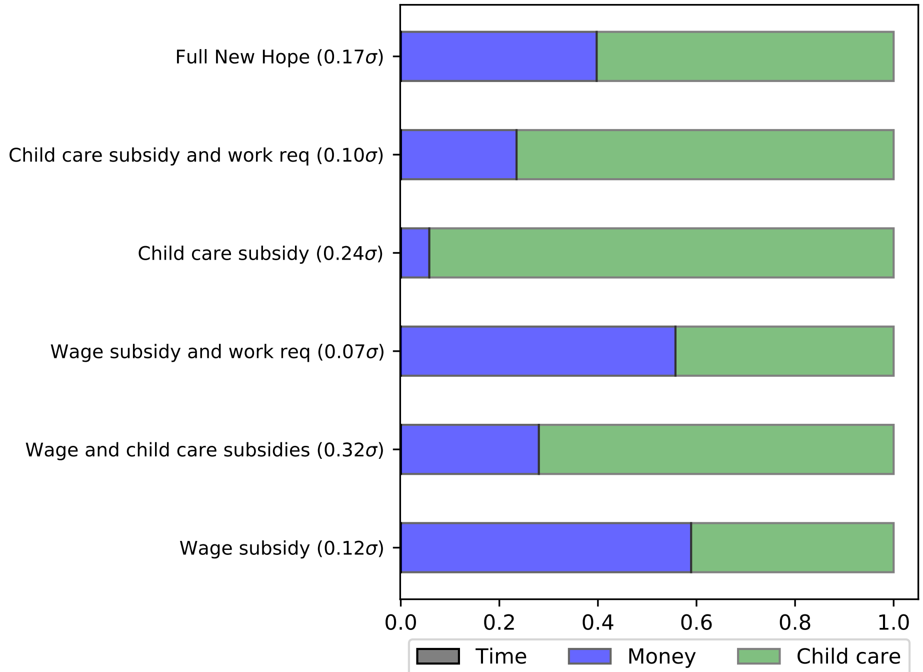
By comparing the effects on the different inputs of policies in isolation versus policies

[51] The mild effects of the work requirements on labor supply resemble effects from (Grogger, 2003) and (Chan, 2013). Both papers, although using different empirical approaches and data, reach similar conclusions about the limited importance of work requirements in explaining the evolution of single mother's labor supply from the 1990s.

together we can study the mechanisms behind the fact that wage and child care subsidies are substitutes in the production of child human capital. In the previous section, I noted that implementing a child care subsidy on top of a wage subsidy increases child human capital by less than the effect of the child care subsidy in isolation. A child care subsidy, when no policy is present, increases child care use by 24 percentage points. Introducing a child care subsidy when the wage subsidy is already in place increases child care use by 20 percentage points, which corresponds to the differences in the simulated effects on child care of a wage and child care subsidy (25 percentage points) and the wage subsidy (5 percentage points). Thus, the fact that two policies are substitutes in the production of human capital is explained given the different choices in child care use associated to each policy.

Figure 8 shows the mediation analysis for different combination of New Hope policies. These policies are the same as those in Table 4. For each case, I decompose the accumulated effect on child human capital up to two years after baseline and further decompose the "explained by self-productivity" component—which captures the share of the effect on current human capital explained by past its past changes—into shares explained by the rest of the inputs. The figure normalizes each effect on human capital (previously shown in Figure 7) to one. For each policy, the bars depict the portion explained by child care, income, and labor supply. For all policies, given the almost null effect of labor supply on child human capital, the share explained by time allocation is almost negligible. Thus, what remains to explain in the effects are the shares accounted by child care and income. When considering the original New Hope policy, the model predicts that most of the effects of the policy on children are explained by child care (61%); this means that, the fact that New Hope parents were able to put their children in center-based child care accounts for the larger portion of the estimated human capital effects. New Hope's effect on household income (net of child care expenditures) accounts for 39% of the effects on child human capital. Besides from the fact that my counterfactual exercises add the child care component, my results are consistent with Agostinelli and Sorrenti (2018) and Nicoletti et al. (2020), who show that the potential negative effects of labor supply of workfare policies are not enough to compensate for the increased income effect.

Figure 8: Mediation analysis: household behavior and the effects of workfare policies on child human capital



Notes: The figure plots the share of the human capital effects of welfare policies explained by changes in household inputs (time, money, and child care). Al effects are normalized to unity. Bars of different colors represents the share explained by the corresponding input. For each policy, in parenthesis, I indicate the simulated effect on child human capital (in σs), two years after baseline.

As the wage subsidy of New Hope and the EITC has similar schedules, we can consider the first as an expansion of the second policy and study which mechanisms drive their effects on children. A children whose parent is exposed to such expansion might end up with more income thanks to the policy shock. If that is the case, the the increased income can be used for child care. Therefore, there are two channels at play: child care use and disposable income (net of child care expenditures). Given the differences in productivity in the production function, these two channels have different effects on child human capital. Figure 8 shows that, even though most of the effects of the EITC-like wage subsidy are indeed explained by income, a non-trivial part of the treatment effects is accounted by child care: the shares explained by income and child care are 60 and 40%, respectively. This finding suggests that the effects of the EITC on child outcomes might depend in part on the availability and quality of center-based child care services. In a related argument, Agostinelli and Sorrenti (2018) find that the negative effects of maternal labor supply on children are concentrated among low-educated families. They interpret this result as finding negative effects for families with limited non-parental care alternatives, such as center-based child care—an insight which is entirely consistent with my results.

These results have direct implications to understand reduced-form effects reported in the literature. Bastian and Michelmore (2018) find long-term effects of EITC schedule shifts on children, while indicating that these effects can be mainly attributed to increases in pre-tax earnings. On the other hand, Michelmore and Pilkauskas (2020) show that EITC effects are mainly concentrated for families of young children and that EITC exposure also changed child care decisions. Thus, it might be the case that these changes in child care choices (although, in the informal margin as their findings suggest) might contribute as well to produce long-term results, as my counterfactual exercises suggest in the context of New Hope.

The analysis shows that the effects of the child care subsidy are almost entirely explained by child care choices. As with the EITC expansion, a child care subsidy can have effects on child human capital through different channels. The subsidy can induce parents not only to use child care but also to increase working hours and thus have more income. Since my simulations predict a relatively small effect of the child care subsidy on labor supply and income (Table 4), the mediation analysis shows that more than 95% of the policy is accounted by the rise in child care use.

The mediation analysis and the study of treatment effects on the inputs of the production function reveal why work requirements have negative effects on child human capital. Even though a policy that includes a work requirement has larger effects on income than a policy without it, the effects on child human capital are lower under the first policy regime. This result is explained because the work requirement's lower effect on child care use and the corresponding detrimental effect on human capital more than compensates the positive effects coming from the requirement's increased income. On the other hand, given the low productivity of time on child human capital, differences in labor supply responses do not play a role in accounting for the effects of work requirements.

Concluding, child care choices have a significant contribution in explaining virtually all of the studied policies. Considering the original policy, child care explains nearly 60% of its effects on child human capital. Even in policies that are often related with parents having more income—such as EITC expansions—child care explains a nontrivial portion of the associated human capital effects.

9 Conclusions

In this paper, I present new evidence on the impact of workfare policies on child outcomes. To this end, I use experimental data from New Hope—an anti-poverty program implemented in Milwaukee (1994-1997) which involved both income and child care subsidies that were tied to a minimum full-time work requirement. With these data, I estimate a dynamic-discrete choice model of the household and child academic human capital. I use the model to explain the channels by which workfare policies impacted child human capital.

The structural framework followed in this paper allows for a better understanding of the separate impacts of income and child care subsidies on child human capital. In the context of this study, most of the effects of New Hope are explained by the child care subsidy component. Moreover, even if we consider a policy that only includes an EITC-like earnings subsidy, a large portion of the impact of such policy on child human capital can be traced back to the increase in child care use. For any policy, I show that requiring full-time work to receive either benefit has a negative effect on child human capital, which is explained by the lower treatment effect on child care probability of the conditioned policy relative to that of the same policy without a full-time work requirement. Hence, my analysis shows that the impact of New Hope—and similar policies—hinges critically on the production of human capital from center-based child care relative to home care.

Two limitations might narrow the scope of my results. First, my findings are only relevant for those who were willing to participate in the New Hope program. Compared to those who were not interested in participating in the program, New Hope's applicants may be better equipped with observed and unobserved characteristics. Second, because of the scale of the New Hope experiment, I cannot analyze general equilibrium effects.[52] Notwithstanding the limitations due to the characteristics of the New Hope experiment, the findings from

[52] These two issues are also likely to be found in papers using structural models to explain findings from randomized controlled trials. See for example Todd and Wolpin (2006), Attanasio et al. (2011), and Attanasio et al. (2015).

this paper suggest that income and child care subsidies have an economically significant potential to impact children's academic achievement through the mediating effects of child care use and that work requirements—by reducing child care use—diminish the positive effect these policies have on child human capital. Future research should quantify the importance of income, labor supply, and child care—and other potential mediators—in explaining the impacts of these policies in more general settings, accounting for general equilibrium effects.

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A The Benefits of New Hope

Table A.1 compares the New Hope benefits to the public system's welfare services. The table illustrates the actual New Hope treatment: the benefits given to participants compared to what the control group had access to. New Hope had three main advantages: it gave an income supplement that was larger than the EITC schedule, it increased the affordable child care supply for low-income working families, and it lowered health care costs.

Table A.1: New Hope versus Wisconsin's social assistance

Components	New Hope (treatment group)	Wisconsin's public services (control group)	New Hope's value-added
Cash assistance	Income supplement: wage subsidy + child allowance.	Earned Income Tax Credit.	Increase disposable income (earnings plus cash assistance) up to 200% depending on the level of annual earnings.
CSJs	New Hope assigned unemployed participants to temporary CSJs.	CSJs available for welfare recipients.	The New Hope CSJs were paid, and it qualified for hours worked to receive New Hope benefits.
Child care	Child care subsidy with a low copayment.	Child care subsidies to welfare receipients and for families in transition out of welfare. Head start was available as well.	Limited supply of public child care slots. In practice, NH increased supply of affordable child care.
Health insurance	Health plans with low copayment through local HMOs.	Medicaid, employer-funded plans.	New Hope complemented employer plans. Also available for families not in AFDC.

Notes: This table summarizes the main components of New Hope. It compares the New Hope benefits with equivalent services available in Wisconsin.

A.1 Income subsidy

The income subsidy is defined as the sum of an earnings subsidy and a child allowance. The earnings subsidy increases at low levels of earnings and phases out (at a slower rate) until reaching zero benefits. Let E be the annual labor earnings for a given year. The earnings subsidy (ES) is determined by the following formula:

$$ES^* = \begin{cases} 0.25 \times E & \text{if } E \leq 8,500 \\ \max\{0.25 \times 8,500 - 0.2(E - 8,500), 0\} & \text{if } E > 8,500, \end{cases}$$

and so the earnings subsidy equals zero at 19,125 dollars. These parameters do not depend on family composition or other sources of income.

Unlike the earnings supplement, the child allowance component considers annual labor earnings at the household level. Let FE denote family earnings and n the number of children in the family. The per-child child allowance (CA) is given by

$$CA = \begin{cases} x_n^* & \text{if } FE < 8,500 \\ \max\{x^* - r(\bar{e})(FE - 8,500), 0\} & \text{if } FE \geq 8,500 \end{cases}$$

where x_n^* is the subsidy maximum level and $r(\bar{e})$ is the phase-our rate. This rate is implicitly defined by the level of earnings at which the child allowance phases out completely ($\bar{e}$).[53] This last parameter is determined as follows:

$$\bar{e} = \begin{cases} 30,000 & \text{if } n < 4 \\ 30,000 + e* & \text{if } n \geq 4 \end{cases}$$

where e^* varies by year of the program (starts at $300 and reaches $2,100 by the third year). The maximum level of child allowance depends on the number of children, as follows:

$$x_n^* = \begin{cases} x_{n-1}^* + (x_{n-1}^* - x_{n-2}^* - 100) & \text{if } n \leq 4 \\ x_{n-1}^* & \text{if } n > 4 \end{cases},$$

where $x_0^* = 0$ (child allowance when the family has no children) and $x_1^* = 1600$. Thus, the maximum level reaches $1,600$ dollars for the first child, an extra $1,500$ for the second, and so on. The maximum subsidy stays fixed at x_4^* for families with more than four children.

The New Hope income supplement ($ES + CA$) complements the EITC. Specifically, let $EITC$ be the amount of EITC for a given level family earnings. The total income supplement (IS) follows:

$$IS = \begin{cases} (ES + CA) - EITC & \text{if } (ES + CA) > EITC \\ 0 & \text{if } (ES + CA) \leq EITC \end{cases}$$

A.2 Child care subsidy

New Hope provided child care vouchers with a relatively low copayment. To have had access to the subsidy, families must have met three basic conditions. First, only individuals with children with children under age 13 were eligible. Second, beneficiaries had to have worked at least 30 hours a week on average in a particular month. For two-parents families, in addition to the full-time requirement of the primary earner, the second earner had to have worked at least 15 hours a week. If the participant had been unemployed, she would have received a subsidy covering a portion of a part-time child care (up to three hours, for a maximum of three weeks). Finally, participants who were eligible to receive the child care benefit were able to enroll their children only in a state- or county-licensed provider. This definition included preschool and daycare centers for younger children and after-school programs for children in school ages.

Let p be the child care cost offerred at a child care facility. The copayment ($\underline{p}$) follows (numbers are in term of monthly dollars):

$$\underline{p} = \begin{cases} 400 & \text{if } p > 400 \text{ and Earnings} \leq 8,500 \\ 315 + 0.01 \times \text{Earnings} & \text{if } p > 400 \text{ and Earnings} > 8,500 \\ p & \text{if } p \leq 400 \end{cases}$$

[53] $r(\bar{e})$ corresponds to the rate r at which $x_n^* - r \times (\bar{e} - 8,500) = 0$.

The New Hope representatives designed a standardize procedure to minimize fraud. Each month, the participant and the provider sign a voucher indicating the hours and the cost of the services. By the end of the month, the child care provider submits these vouchers to New Hope representatives to receive their payments. New Hope pays the subsidy directly to the child care provider. The participant pays the copayment to the provider as well. If the participant does not submit the wage stubs, New Hope would cover only 75% of the child care cost of the month. If the participant does not submit the wage stub for the second month in a row, New Hope reps would suspend the subsidy.

A.3 Community Service Jobs (CSJ)

New Hope staff advised participants in finding local job openings. If after a period of eight weeks the participant had not find a job, New Hope would assigned her to a paid CSJ for a maximum of six months.[54] The CSJ's paid was minimum wage. Importantly, the hours worked in these CSJs qualified for the income supplement, child care subsidy, and the health insurance subsidy.

According to Brock et al. (1997), other forms of CSJs were available at that time in Milwaukee. However, unlike the New Hope program, these types of CSJs did not qualify for the state's EITC. Indeed, the state CSJs positions were meant for individuals who needed them to receive welfare grants, not as a mean to earn a salary. The New Hope CSJs were given to people regardless of their employment status, while the state CSJs were not usually offered to unemployed individuals.

A.4 Health insurance

New Hope financed part of the health insurance for workers with no employer-granted health insurance or Medicaid. To have access to the health insurance, individuals must have worked at least 30 hours a week every month. If a participant became unemployed or reduce her working hours below 30, New Hope kept their health insurance up to three weeks.[55]

New Hope provided health insurance through a Health Maintenance Organizations (HMO). The program's representatives displayed a number of plans and explained in detail the ups and downs of every plan. Beneficiaries would pick from any of those plans. Most of the participants choose to stay with the HMO that had a contract with Milwaukee County to provide Medicaid services.

To receive health insurance through New Hope, participants had to pay a small share of its cost. The copayment was a function of household income and size. The copay began at $72 and $168 a year for a single person and households with three members or more. The maximum copay was $600 and $1,548 for single- and three-person households, respectively. If an individual had an employer health plan, New Hope would cover for the difference between the insurance's premium and the New Hope copayment. Moreover, if the participant did not have a dental coverage under her employer health plan, she had the option of choosing from the New Hope available dental plans.

Many of participants opted out from the New Hope health insurance plan, as some families choose Medicaid instead. To be eligible to Medicaid, families under AFDC had to make less

[54] The Milwaukee Private Industry Council acted as the former employer, although funds came from New Hope.

[55] In practice, New Hope representatives would kept the health insurance eligibility up to three months if the participant would have demonstrated active job search efforts.

than 185% the federal poverty line.[56] As many New Hope families met these requirements and given that Medicaid had no premiums, the Medicaid option seemed more convenient. Nonetheless, take-up was still considerable: 47.6% of participants were covered by a New Hope health insurance at some point during the 36-months eligibility period.

[56] After PRWORA, individuals that were eligible to Medicaid as of August 1996 maintained their eligibility status.

B Baseline Characteristics across Samples

Table B.1: Baseline characteristics: CFS sample

Variable	(1) Treatment	(2) Control	(3) T-C
Age	29.04	28.53	0.51
	[7.14]	[6.64]	(0.52)
Female (%)	90.12	91.74	-1.62
	[29.89]	[27.57]	(2.18)
African-American, non-Hispanic (%)	58.14	53.85	4.29
	[49.40]	[49.92]	(3.77)
Hispanic (%)	27.03	29.06	-2.02
	[44.48]	[45.47]	(3.41)
White, non-Hispanic (%)	10.47	14.53	-4.06
	[30.65]	[35.29]	(2.51)
Others (%)	4.36	2.56	1.80
	[20.45]	[15.83]	(1.39)
Never married (%)	62.21	62.39	-0.18
	[48.56]	[48.51]	(3.68)
Married living w/ spouse (%)	11.05	9.69	1.36
	[31.39]	[29.62]	(2.31)
Married living apart (%)	9.88	11.11	-1.23
	[29.89]	[31.47]	(2.33)
Separated, divorced or widowed (%)	16.86	16.81	0.05
	[37.49]	[37.45]	(2.84)
Highschool diploma or GED (%)	50.00	45.87	4.13
	[50.07]	[49.90]	(3.79)
Highest grade completed	11.24	11.10	0.14
	[2.15]	[2.04]	(0.16)
$0 (%)	36.63	36.75	-0.12
	[48.25]	[48.28]	(3.66)
$1-999 (%)	16.86	14.53	2.33
	[37.49]	[35.29]	(2.76)
$1,000-4,999 (%)	23.26	23.65	-0.39
	[42.31]	[42.55]	(3.22)
$5,000-9,999 (%)	13.66	14.81	-1.15
	[34.40]	[35.58]	(2.66)
$10,000-14,999 (%)	6.98	6.84	0.14
	[25.51]	[25.28]	(1.93)
$15,000 or more (%)	2.62	3.42	-0.80
	[15.99]	[18.20]	(1.30)

Notes: This table compares baseline characteristics of treatment and control groups. The variables were measured at baseline. The last six rows present the proportion of individuals in different groups defined by labor earnings (past 12 months). I show sample means of each variable for treatment and control group in columns 1 and 2. The third column tests the null hypothesis that the means are equal. The sample corresponds to participants in the CFS sample. The first two columns present standard deviations in square brackets. In the third column, robust standard errors are in parenthesis. *,**,*** indicates significance at the 10, 5, and 1% level.

Table B.2: Baseline characteristics: estimation sample

Variable	(1) Treatment	(2) Control	(3) T-C
Age	28.47	28.11	0.36
	[6.88]	[6.33]	(0.55)
Female (%)	100.00	100.00	0.00
	[0.00]	[0.00]	-
African-American, non-Hispanic (%)	56.64	53.85	2.80
	[49.64]	[49.94]	(4.12)
Hispanic (%)	27.62	28.43	-0.81
	[44.79]	[45.18]	(3.72)
White, non-Hispanic (%)	11.54	15.38	-3.85
	[32.00]	[36.14]	(2.83)
Others (%)	4.20	2.34	1.85
	[20.08]	[15.15]	(1.47)
Never married (%)	63.99	63.21	0.78
	[48.09]	[48.30]	(3.99)
Married living w/ spouse (%)	8.39	8.36	0.03
	[27.77]	[27.73]	(2.30)
Married living apart (%)	11.19	11.37	-0.18
	[31.58]	[31.80]	(2.62)
Separated, divorced or widowed (%)	16.43	17.06	-0.62
	[37.12]	[37.68]	(3.09)
Highschool diploma or GED (%)	49.30	44.82	4.48
	[50.08]	[49.81]	(4.13)
Highest grade completed	11.30	11.08	0.22
	[2.02]	[2.05]	(0.17)
$0 (%)	37.76	38.80	-1.03
	[48.56]	[48.81]	(4.03)
$1-999 (%)	17.13	16.05	1.08
	[37.75]	[36.77]	(3.08)
$1,000-4,999 (%)	23.78	23.75	0.03
	[42.65]	[42.62]	(3.53)
$5,000-9,999 (%)	12.59	13.71	-1.12
	[33.23]	[34.46]	(2.80)
$10,000-14,999 (%)	6.29	6.02	0.27
	[24.33]	[23.83]	(1.99)
$15,000 or more (%)	2.45	1.67	0.78
	[15.48]	[12.84]	(1.17)

Notes: This table compares baseline characteristics of treatment and control groups. The variables were measured at baseline. The last six rows present the proportion of individuals in different groups defined by labor earnings (past 12 months). I show sample means of each variable for treatment and control group in columns 1 and 2. The third column tests the null hypothesis that the means are equal. The sample corresponds to participants in the CFS sample who responded the second-year survey. The first two columns present standard deviations in square brackets. In the third column, robust standard errors are in parenthesis. *,**,*** indicates significance at the 10, 5, and 1% level.

Table B.3: Baseline characteristics: estimation sample (parents of young children)

Variable	(1) Treatment	(2) Control	(3) T-C
Age	25.78	26.34	-0.56
	[5.51]	[6.14]	(0.62)
Female (%)	100.00	100.00	0.00
	[0.00]	[0.00]	-
African-American, non-Hispanic (%)	53.29	52.38	0.91
	[50.04]	[50.08]	(5.32)
Hispanic (%)	29.94	30.69	-0.75
	[45.94]	[46.24]	(4.90)
White, non-Hispanic (%)	13.17	13.76	-0.58
	[33.92]	[34.54]	(3.64)
Others (%)	3.59	3.17	0.42
	[18.67]	[17.58]	(1.92)
Never married (%)	71.86	69.84	2.02
	[45.11]	[46.02]	(4.84)
Married living w/ spouse (%)	4.79	7.41	-2.62
	[21.42]	[26.26]	(2.56)
Married living apart (%)	7.19	10.58	-3.40
	[25.90]	[30.84]	(3.04)
Separated, divorced or widowed (%)	16.17	12.17	4.00
	[36.93]	[32.78]	(3.69)
Highschool diploma or GED (%)	50.90	50.26	0.63
	[50.14]	[50.13]	(5.32)
Highest grade completed	11.35	11.21	0.14
	[1.69]	[2.11]	(0.20)
$0 (%)	37.13	39.15	-2.03
	[48.46]	[48.94]	(5.17)
$1-999 (%)	20.36	16.93	3.43
	[40.39]	[37.60]	(4.13)
$1,000-4,999 (%)	23.35	25.40	-2.04
	[42.44]	[43.64]	(4.58)
$5,000-9,999 (%)	12.57	13.23	-0.65
	[33.26]	[33.97]	(3.57)
$10,000-14,999 (%)	2.99	4.23	-1.24
	[17.09]	[20.19]	(2.00)
$15,000 or more (%)	3.59	1.06	2.53
	[18.67]	[10.26]	(1.57)

Notes: This table compares baseline characteristics of treatment and control groups. The variables were measured at baseline. The last six rows present the proportion of individuals in different groups defined by labor earnings (past 12 months). I show sample means of each variable for treatment and control group in columns 1 and 2. The third column tests the null hypothesis that the means are equal. The sample corresponds to participants in the CFS sample who responded the fifth-year survey. The first two columns present standard deviations in square brackets. In the third column, robust standard errors are in parenthesis. *,**,*** indicates significance at the 10, 5, and 1% level.

Table B.4: Baseline characteristics: estimation sample (with information on child academic achievement)

Variable	(1) Treatment	(2) Control	(3) T-C
Age	29.85	29.36	0.49
	[6.02]	[5.74]	(0.83)
Female (%)	100.00	100.00	0.00
	[0.00]	[0.00]	-
African-American, non-Hispanic (%)	59.79	55.66	4.13
	[49.29]	[49.91]	(6.97)
Hispanic (%)	22.68	27.36	-4.68
	[42.09]	[44.79]	(6.12)
White, non-Hispanic (%)	13.40	15.09	-1.69
	[34.24]	[35.97]	(4.94)
Others (%)	4.12	1.89	2.24
	[19.99]	[13.67]	(2.39)
Never married (%)	59.79	61.32	-1.53
	[49.29]	[48.93]	(6.90)
Married living w/ spouse (%)	11.34	13.21	-1.87
	[31.87]	[34.02]	(4.64)
Married living apart (%)	12.37	7.55	4.82
	[33.10]	[26.54]	(4.19)
Separated, divorced or widowed (%)	16.49	17.92	-1.43
	[37.31]	[38.54]	(5.33)
Highschool diploma or GED (%)	49.48	44.34	5.14
	[50.26]	[49.91]	(7.04)
Highest grade completed	11.40	10.82	0.58*
	[2.68]	[2.05]	(0.33)
$0 (%)	38.14	34.91	3.24
	[48.83]	[47.89]	(6.79)
$1-999 (%)	13.40	16.04	-2.64
	[34.24]	[36.87]	(5.01)
$1,000-4,999 (%)	25.77	18.87	6.91
	[43.97]	[39.31]	(5.85)
$5,000-9,999 (%)	10.31	19.81	-9.50*
	[30.57]	[40.05]	(5.03)
$10,000-14,999 (%)	9.28	8.49	0.79
	[29.16]	[28.01]	(4.01)
$15,000 or more (%)	3.09	1.89	1.21
	[17.40]	[13.67]	(2.19)

Notes: This table compares baseline characteristics of treatment and control groups. The variables were measured at baseline. The last six rows present the proportion of individuals in different groups defined by labor earnings (past 12 months). I show sample means of each variable for treatment and control group in columns 1 and 2. The third column tests the null hypothesis that the means are equal. The sample corresponds to participants in the CFS sample who responded the fifth-year survey. The first two columns present standard deviations in square brackets. In the third column, robust standard errors are in parenthesis. *,**,*** indicates significance at the 10, 5, and 1% level.

C Computation of Main Household and Child Outcomes Variables for Reduced-Form Analysis

C.1 Child care

I construct the child care variable using the New Hope surveys. In the second-year survey, individuals were asked about all regular child care arrangement for the past two years. Possible child care arrangements in the survey were: (i) Head Start; (ii) preschool, nursery school, or a child care center other than Head Start; (iii) school-based extended day program; (iv) another child care other than in someone's home; (v) a person other than a member of the household; (vi) another member of the family of household; and (vii) no arrangements. Participants reported the number of months spent in each case (except for number (vii)). I consider a formal child care arrangement categories (i)-(iv), and an informal child care the rest of them. I define $cc_t = 1$ if the child (as declared by the parent) spent the maximum number of months in categories (i)-(iv), and 0 otherwise. Using this information, I obtain child care choices for period $t = 1$ (even though this question would cover both period $t = 0$ and $t = 1$).

To recover child care choices at the fifth year, the procedure is similar. In this year, the child care options are: (i) by someone 16 years of age or younger; (ii) by an adult at home; (iii) by an adult in someone else's home; (iv) in a child care center, before or after school program, community center, or Head Start; (v) child's own supervision; (vi) by sibling; (vii) others. I define $cc_t = 1$ (for period $t = 4$) if the child spent the higher number of months in (iv).

C.2 Income

I construct a proxy for family income using administrative information on the different sources of income. I define household income for individual i at year t as follows:

$$I_{it} = E_{it} + EITC_{it} + D_i(Sup_{it} + CSJ_{it}) + W_{it},$$

where E_{it} are labor earnings, $EITC_{it}$ is the earned income tax credit, D_i the treatment group dummy, Sup_{it} is the New Hope income supplement, CSJ_{it} are earnings from CSJs, and W_{it} are welfare payments. Sup_{it} and CSJ_{it} can be earned only by the treatment group. The Unemployment Insurance system (UI) of the State of Wisconsin collects quarterly data of E_{it}. I construct yearly measures of the nominal values of E_{it} to simulate the corresponding amount of EITC for every family. Finally, New Hope administrative data has information on Sup_{it} and CSJ_{it} on a quarterly basis.[57] For all period, I express income (after simulating the EITC) as annual 2003 dollars. Finally, W_{it} contains Food Stamps money and AFDC (replaced by "Wisconsin Works" after TANF) cash transfers.

Family income from administrative databases does not include several sources of income. Some of the excluded source of income are the unemployment insurance, child support, and others payments from social programs. Furthermore, it does not consider income from other family members. The New Hope surveys collect these and others sources of income. Unfortunately, the New Hope surveys do not track income for every year. Additionally, the year-two survey only asks about "last month's income," so income from administrative sources and surveys cannot be directly compared.

[57] The income of the New Hope CSJs does not show up in the UI records. The CSJs that New Hope offered were limited in time (no longer than 6 months), and so they were not eligible to UI.

C.3 Labor supply

I define the employment measure using the Wisconsin UI records and the New Hope client database containing earnings in New Hope Community Service Jobs (CSJ). The employment dummy equals 1 if there is a positive wage in the UI or client database in a given period, and 0 otherwise.

C.4 Child outcomes

The Teachers' reports contain have information on teachers' perceptions about the child academic outcomes. It has data on three measures: the academic subscale of the Social Skills Rating System (SSRS), the Classroom Behavior Scale and the Mock reports cards. In this paper, I use the SSRS academic subscale (Gresham and Elliot, 1990). In the SSRS, the teacher ranks the child in several subjects. These are reading skills, math, intellectual functioning, motivation, oral communication, classroom behavior, parental encouragement, and overall academic performance—which is the item I use in this paper. Each variable takes the following values: 1 (bottom 10%), 2 (next lowest 20%), 3 (middle 40%), 4 (next highest 20%), and 5 (highest 10%).

D Welfare parameters

In this appendix, I show the welfare functions that determine disposable income (equation 6). I consider three policies: the EITC, AFDC, and Food Stamps (SNAP) payments.

D.1 The EITC

The EITC parameters vary by state, year, and the number of children (k_t). Denote annual gross earnings as $E_t = w_t h_t \times 52$. Following Chan (2013), there are four key parameters for the federal EITC: the phase-in and phase-out rates ($r^k_{1,t}$ and $r^k_{2,t}$), and the bracket thresholds ($b^k_{1,t}$ and $b^k_{2,t}$), where the index k denote the number of children. k goes from 1 to 3, since the parameters of the EITC schedule do not vary for families with more than three children. In year t and for a family with $k_t = k$ number of children, the federal EITC payment ($EITC^f_t$) follows:

$$EITC_t = \begin{cases} r^k_{1,t} E_t & \text{if } E_t < b^k_{1,t} \\ r^k_{1,t} b^k_{1,t} & \text{if } b^k_{1,t} \leq E_t < b^k_{2,t} \\ \max\left\{ r^k_{1,t} b^k_{1,t} - r^k_{2,t}(E_t - b^k_{2,t}), 0 \right\} & \text{if } E_t \geq b^k_{2,t} \end{cases}$$

In the case of Wisconsin, the state EITC payment ($EITC^s_t$) is determined as a fraction of the federal payment: $r^k_{s,t} EITC^f_t$, where $0 < r^k_{s,t} < 1$ varies by number of children and year. The total EITC payment equals $EITC_t = EITC^f_t + EITC^s_t$.

D.2 The AFDC and TANF

The AFDC parameters vary by family composition and year. Starting 1997, the state of Wisconsin implemented "Wisconsin Works" (W-2), under the TANF umbrella. Instead of giving cash transfers like most states did, W-2 offered paid CSJs for up to five years. In terms of the model then, a W-2 salary becomes part of the potential wage offer (equation 4).

Until 1996 (that is, periods $t = 0$ and $t = 1$), the standard AFDC program was in place. Let B^*_t be the cash transfer an individual under welfare could get, given by:

$$B^*_t = \max\left\{ \min\left\{ \overline{B}, \overline{B} - (E_t - 30) \times .67 \right\}, 0 \right\},$$

where $\overline{B}$ is the so-called "benefit standard," the maximum amount of welfare an individual is entitled to. Individuals enter the program if $E_t \leq c$. The parameters c and $\overline{B}$ vary by family size and state.[58] This formula captures the \$30-and-a-third policy implemented in 1967: The recipient may keep the first 30 dollars she makes. Above that value, for each dollars she earns, she must "pay a tax" of 0.67 (the marginal tax rate is 67%). In practice, the formula is designed for monthly figures, so I adapted parameters to accommodate for annual income.

D.3 SNAP

The Supplemental Nutrition Assistance Program (SNAP)—formerly known as Food Stamps—is the largest nutrition program in the U.S. The program provides money vouchers to eligible individuals to spend food in grocery stores.

Unlike the AFDC, SNAP eligibility and voucher parameters have not changed much in time. It does not vary by state either. Let E_n be net income, E gross earned income, B welfare

[58] The exact values can be found at the Welfare Rules Database for Wisconsin, Area 1.

payments (including AFDC and New Hope cash transfers), SD a standard deduction, and e the poverty guideline. To receive SNAP, a household must meet the gross and net income tests:[59]

$$E < 1.3e,$$

$$E_n < e,$$

where net income follows[60]

$$E_n = 0.8E + B - SD$$

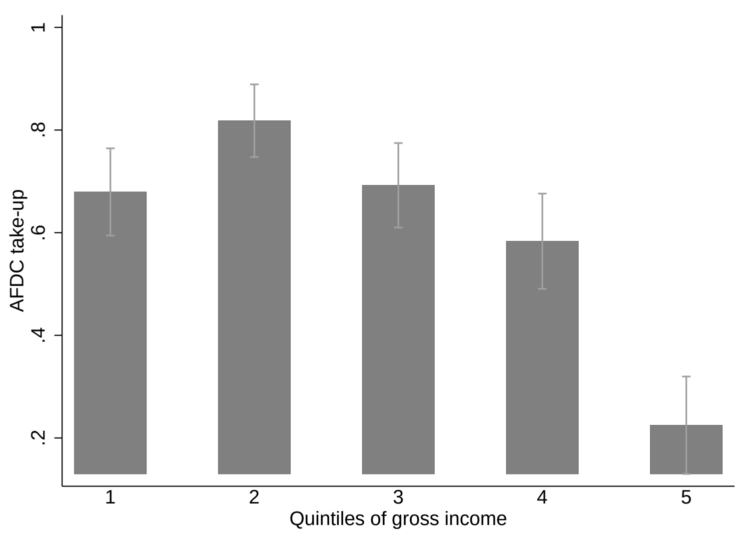
The SNAP benefits are determined by the following formula:

$$S^* = \max\left\{MaxB - 0.3E_n, 0\right\},$$

where $MaxB$ is the Maximum allotment. All income thresholds and other parameters are adjusted following Social Security's Cost-of-Living Adjustments.

D.4 Take-up rates of AFDC and SNAP

Figure D.1: Take-up rate of AFDC

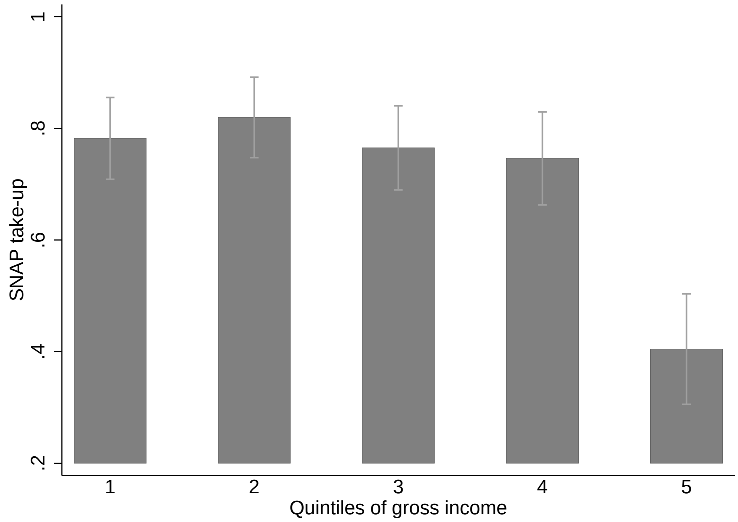


Notes: The figure shows the estimated take-up rate across gross income quintiles during the year of random assignment (1994-1995). The take-up rate is defined as the proportion of eligible families who received a AFDC payment during the year. Gross income corresponds to the sum of quarterly earnings in the year of random assignment. The bars show the point estimate of the take-up rate with a 95% boostrap confidence interval (1,000 draws).

[59]Also, if a family is living only with AFDC payments, then it is automatically eligible. For the purpose of this paper, I assume that if a participant is not working, then she is eligible for SNAP payments.

[60]The actual formula includes a standard shelter deduction, which I assume to be zero for all families.

Figure D.2: Take-up rate of SNAP



Notes: The figure shows the estimated take-up rate across gross income quintiles during the year of random assignment (1994-1995). The take-up rate is defined as the proportion of eligible families who received at least one SNAP check over the course of the year. Gross income corresponds to the sum of quarterly earnings in the year of random assignment. The bars show the point estimate of the take-up rate with a 95% boostrap confidence interval (1,000 draws).

E Details on Data for Structural Estimation

E.1 Data for estimation

To obtain the trajectories of the key variables of the model, I combine administrative and survey data. Administrative data is available throughout the period (from baseline until eight years after), while surveys were collected only at specific years (two, five, and eight years after baseline). This section describes how I combine data from different sources to construct the main variables predicted by the model.

Weekly hours worked. Using the second-year survey, I compute the average hours worked in a week for the baseline and one year after random assignment ($t = 0$ and 1). In this survey, individuals reported the usual hours worked in every job they had in the last two years (thus, covering baseline and year $t = 1$). For every job they had, respondents reported weekly hours worked at the beginning and at the end of the job. Using the reported dates for each job spell, I compute monthly weekly hours worked. If more than one job was reported in a particular month, I assume that there are no overlapping in spells and take the average of all jobs. If the individual did not report having a job in a particular month, I set hours worked to zero. Then, for each calendar year, I compute the annual average of weekly hours worked—including the zeros corresponding to the months that the individual did not work. From the fifth- and eighth-year surveys, I recover the hours worked from periods $t = 4$ and 7. In these surveys, individuals reported the average hours worked at the current or most recent job in the last 12 months. I weight the reported average hours worked by the share of quarters employed in a year. I compute this variable using administrative data from the UI database and calculating the proportion that individuals stayed employed in year ($4^{-1} \sum \mathbf{1}\{wage_q > 0\}$, where $wage_q$ is quarterly labor earnings). Finally, I discretize hours worked variable in three categories: 0 if hours worked equals 0, 15 if hours is greater than 0 but less than 30, and 40 if hours worked is above 30.

Hourly wages. I combine administrative with survey data to compute weekly average gross earnings (in the numerator) and weakly average hours worked (in the denominator). I obtain weekly average gross earnings by averaging quarterly earnings in a particular year (from the UI data) with any salary earned in a CSJ (for those in the treatment group), adjusted to 2003 dollars. I divide weekly earnings by average hours worked in a week from survey data (see paragraph above). Because hours worked are available for period $t = 0, 1, 4$ and 7, so is hourly wages. For $t = 4$ and $t = 7$, the state CSJs from TANF enter the pool of possible wage offers. Thus, I incorporate the CSJs payments in the hourly wage calculation of $t = 4$ and $t = 7$.

Child care use. See Appendix (C.1) for details on the construction of the child care variable.

Family consumption. To construct annual family consumption, I use information on (i) total income, (ii) child care payments, and (iii) family composition. First, I obtain total annual income as the sum of UI earnings, AFDC or TANF payments (depending on the year), and potential EITC payments. The first three sources of income are observed from administrative data, while for the last source I compute the potential EITC payment following the EITC schedule and assuming full take-up. Second, I compute child care payments as the previous paragraph describes. Then, total family consumption in a year equals total income minus child care payments. These monetary values are expressed in 2003 dollars. Finally, to compute per-capita consumption I divide total family consumption by the household size (parents and number of children).

Child human capital. I use the set of SSRS variables to measure child academic performance (see Appendix C.4).

E.2 Auxiliary model

Table E.1: Target moments

Moments	**Simulated**	**Data**	**S.E. data**
A. Labor supply and child care decisions			
$Pr(\text{child care}_t \mid RA = 0)$, $t = 1$ age ≤ 6	0.403	0.435	0.040
$Pr(\text{free child care} \mid \text{child care} = 1, \text{eligible}, RA = 0)$	0.597	0.526	0.059
Pr(part-time work)	0.333	0.340	0.017
Pr(full-time work)	0.287	0.263	0.017
B. Individual: $log(wage_t) = X_t'\beta + \epsilon_t$			
Coefficient on high school dummy	0.237	0.236	0.069
Coefficient on time trend	0.082	0.086	0.010
Constant	1.604	1.594	0.069
σ^2	0.381	0.379	0.085
AR(1) shock (ρ)	0.304	0.287	0.083
C. Spouse: $log(wage_t) = X_t'\beta + \epsilon_t$ and employment			
High school dummy	0.165	0.101	0.147
Constant	7.194	7.205	0.101
σ^2	0.227	0.261	0.066
Employment probit	0.178	0.186	0.027
D. SSRS and household choices			
$Corr[SSRS_2, SSRS_5]$ young	0.559	0.477	0.115
$Corr[\text{income}_1, SSRS_2]$ young	0.081	0.048	0.059
$Corr[\text{hours worked}_1, SSRS_2]$ young	0.077	0.133	0.058
$Corr[SSRS_2, SSRS_5]$ old	0.480	0.471	0.065
$Corr[\text{income}_1, SSRS_2]$ old	0.014	0.000	0.049
$Corr[\text{hours worked}_1, SSRS_2]$ old	0.000	-0.007	0.050
$E[SSRS \mid \text{child care}_t = 1] - E[SSRS \mid \text{child care}_t = 0]$	0.339	0.277	0.173
$Var(SSRS)$	0.988	0.977	0.035
$Corr(SSRS_2, \text{initial wage})$	0.042	0.004	0.062

Notes: This table compares the simulated and observed estimated moments that are targeted in estimation. $SSRS_t$ corresponds to overall SSRS measure of academic achievement in period t. In this measure, teachers rank children in a five-point scale based on the overall academic performance in the classroom. $time_t$ corresponds to time with the child (τ_t from equation 3). cc_t is child care in period t for children who are less than six years old. The rest of the variables are constructed following Appendix E.1.