Understanding the Effects of a Work-Based Welfare Policy on Child Human Capital*

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August 3, 2018

Abstract

In Milwaukee, Wisconsin (1994-1997), a work-based, anti-poverty intervention, "New Hope," randomly assigned an income subsidy—similar to the EITC—and a child care subsidy subject to a full-time work requirement to a group of economically disadvantaged families. Randomly chosen applicants had access to these benefits for three years. The experimental evaluation found positive effects of the program on labor supply, income, and child care use. Furthermore, while parents were eligible, the program also boosted various measures of child academic achievement. However, since policies were given in a single package, little is known about the mechanisms by which New Hope affected child outcomes. This paper disentangles the mechanisms that explain the impact of New Hope on the human capital of children who were young while their families were under New Hope. To this end, I estimate a dynamic-discrete choice model of the household and child human capital. Counterfactual experiments indicate that the bulk of the impact of New Hope on child human capital is explained by the child care subsidy component of the New Hope package: the impact of the child care subsidy on child human capital is 97% bigger than that of the income subsidy. If New Hope had not included a full-time work requirement, the effect of the program on child human capital would have been almost 40% bigger.

*I am indebted to Magne Mogstad, Derek Neal, and Alessandra Voena for providing guidance and feedback throughout this project. I also thank Thibaut Lamadon, Petra Todd, Steve Levitt, Stephane Bonhomme, James Heckman, and seminar participants at the SOLE annual meeting, North American Summer Meeting of the Econometric Society, University of Chicago, Universidad Diego Portales, Universidad de los Andes, and Pontificia Universidad Católica. A previous version of this paper circulated under the title "Understanding the Effects of Income and Child Care Subsidies on Children's Academic Achievement."

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1 Introduction

Around the world, policymakers have used a variety of strategies to encourage the labor market participation of individuals from low socioeconomic background. In the U.S., prominent examples of such policies include imposing work requirements and time limits to access welfare, income subsidies such as the Earned Income Tax Credit (EITC), and child care subsidies such the Child Care Development Fund (CCDF).[1] The empirical evidence indicates that some of these policies have succeeded in meeting their original goals—namely, to promote work and increase family income.[2] However, these policies could have unintended, negative consequences on child outcomes: parents could opt for center-based child care, increase the time spent in the labor market, and reduce the time caring for children.[3]

Some of the most compelling evidence on the effects of work-based welfare programs comes from a randomized controlled trial called New Hope. The program assigned applicants (over 18 years old) to a policy bundle that included an income subsidy—similar to the EITC—and a child care subsidy—which resembled the CCDF. To have access to any of these benefits, participants had to prove having worked full time in a given month. For those applicants with children who were young while New Hope was running, the program increased family income by 6%, 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

[1] In 1996, the Personal Responsibility and Work Opportunity Act imposed stronger work requirements and time limits in the new Temporary Assistance for Needy Families (TANF) relative to what the older Aid to Families with Dependent Children required. The CCDF is a block grant to states for the provision of child care vouchers to low-income working parents. This program was conceived as a complement to TANF that would facilitate welfare-to-work transitions. The EITC is a mean-tested cash transfer program for low-income families. 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) 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 receipient'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.

also boosted various measures of child academic achievement.[4] New Hope's experimental design provides reliable evidence on the program's causal effects on children's academic achievement—a crucial input for public policy purposes. Nonetheless, because all policies were bundled together, on cannot assess the role played by each individual policy component of New Hope in the associated changes on household choices and child outcomes.[5]

This paper disentangles the mechanisms that explain the impact of New Hope on child human capital for children who were young while their parents were eligible to New Hope. To address the empirical limitations of the experimental evidence, I estimate a dynamic-discrete choice model of the household 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). Child human capital production follows a dynamic process, where household decisions and the current stock of child human capital are inputs in this production function. The household's budget set encompasses different mean-tested programs, including the AFDC, the EITC, and New Hope. I estimate the model using non-experimental moments while leaving experimental estimates for model validation. I exploit the estimated model to evaluate how New Hope policies impacted household choices and thereby child human capital. I show that New Hope's effects on child human capital are almost entirely explained because parents took their children to center-based child care, induced primarily by the child care subsidy component of the program. More broadly, overall lessons from this paper are relevant to the design and evaluation of welfare policies seeking to uplift families out of poverty by inducing, or directly requiring, work.[6]

The structural estimates reveal that center-based child care has a relatively large effect

[4]See Bos et al. (1999), Huston et al. (2003), and Miller et al. (2008) for evidence on the effects of New Hope on child and family outcomes for the overall sample. In Rodriguez (2018), I show novel evidence on the effects of the program for applicants with children who were six years of age or less two years after baseline. This present paper focuses on the sample of young children while New Hope was in effect.

[5]Grogger and Karoly (2009) conclude that experimental studies on welfare reforms and child well-being yield mixed results, where the estimated effects are likely to depend on each program's characteristics.

[6]In 2018, the Trump administration signed an executive order encouraging federal agencies to promote work by toughening work requirements; by either enforcing the ones that are actually in place, revising those with waivers, or adding to programs who lack. Furthermore, the Trump administration have signed off waivers in order for state governments to include work requirements for Medicaid.

on child human capital. The estimated human capital production function imply that giving an average family an amount of money equal to the cost of child care raises child human capital by 0.8% of a standard deviation—this is the pure "money" effect. In contrast, using the same amount of money for purchasing child care services increases child human capital by 52% of a standard deviation. Consistently, a mediation analysis shows that more than 100% of the effects of New Hope on child human capital are mediated by the policy-induced increase in child care use.

I assess the role played by each policy component of New Hope in explaining the treatment effects on child human capital. The child care subsidy explains most of the effects of New Hope on child human capital. Compared to the income subsidy, the child care subsidy produces 97% more stock of child human capital. Looking at the household behavioral changes explaining the effects of both counterfactual policies, I find that the income subsidy has larger effects on consumption (not used on child care) and the child care subsidy has bigger effects on child care use. Therefore, the larger productivity of child care in the production function explains why the child care subsidy has bigger effects on child human capital.

The full-time work requirement has a negative effect on child human capital. The effects of the program would have been larger (0.04 standard deviations of child human capital) if New Hope had not included a work requirement. For the most part, the negative effect of the work requirement is explained because this policy—relative to a program without this condition—decreases the treatment effect on child care use.

This paper contributes to the early New Hope literature (Huston et al., 2001, 2005, 2011). This group of studies show sizable effects of the policy on the academic achievement of participant's children. Nonetheless, clearer public-policy implications regarding impacts on children could not be made as policies were conceived as one unique bundle. The structural framework I provide allows for simulating the effects on children of the individual New Hope policies as well as revealing potential complementarities between them.

In addition, this paper offers new results to a broader literature studying mean-tested programs and child outcomes. First, the literature studying child care subsidies have found that these policies have a relatively large effect on children from low socioeconomic background (Havnes and Mogstad, 2015; Heckman and Mosso, 2014; Cornelissen et al., 2017), which is line with the estimated effects of the New Hope child care subsidy I report in this paper. Second, I complement the literature on income and child outcomes by providing new evidence on the mechanisms explaining the effects of New Hope income subsidy and the EITC on child outcomes (Dahl and Lochner, 2012; Maxfield, 2013; Hoynes et al., 2015; Manoli and Turner, 2015; Bastian and Michelmore, 2017). Third, I add to a relatively scarce literature on the effects of work requirements on household behavior. I show that work requirements have positive but limited effects on labor supply, in line with other studies (Grogger, 2003; Chan, 2013). Further, I present novel results on the effects of work requirements on child outcomes.

On the methodological side, I build upon the literature that combines experimental or quasi-experimental evidence with structural models (Bajari and Hortaçsu, 2005; Todd and Wolpin, 2006; Keane and Wolpin, 2007; Attanasio et al., 2011; DellaVigna et al., 2012; Attanasio et al., 2015; Voena, 2015; Autor et al., 2017). Following this line of research, my framework advances reduced-form studies by delineating the mechanisms that explain the observed policy treatment effects obtained by either experimental or quasi-experimental methods. I also contribute to the structural literature on household behavior and child welfare by exploiting experimental data to validate the model's capacity to predict the impact of different welfare policies (Bernal, 2008; Brown and Flinn, 2011; Del Boca et al., 2013; Brilli, 2014; Del Boca et al., 2014; Mullins, 2015; Bruins, 2016).[7]

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. Section 4 outlines the available reduced-form evidence on New Hope. Section 5 presents the dynamic-discrete

[7]This literature uses survey data to estimate structural models and non-experimental moments as model validation.

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 deepened the incentive to work that families were subjected to at the time the program was implemented.[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 have a household income equal to or less than 150% of the federal poverty line.[11] Additionally, 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).[12] Beginning at baseline recruitment and lasting for 36 months, a randomly selected group of applicants had access to various benefits. To receive any of the subsidies of the program in a given month, the participants had to prove that they had worked at least 30 hours a week on average. To enforce this requirement, New Hope agents asked applicants—each 5th day of

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

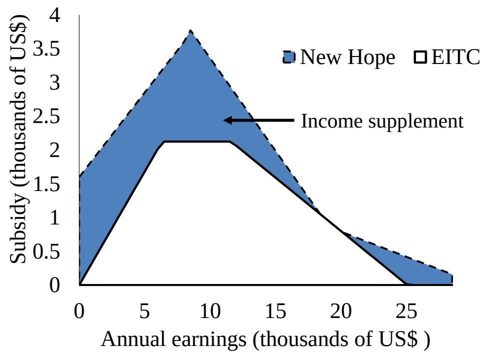
[9] Applicants came from the north and south side of the U.S. Highway 94 and the Menomenee River Valley. The New Hope team selected those neighborhoods (which were defined by their postal zip codes) because they had a relatively high poverty rate and ethnically diverse populations. Each area had about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

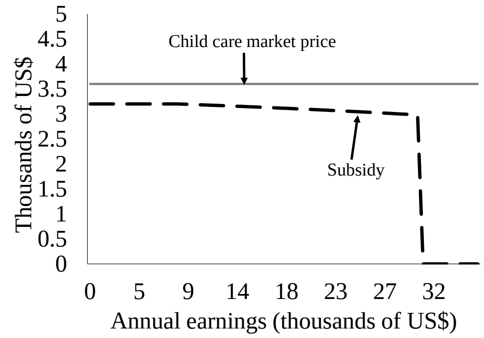
[11] For a household with one adult and two children, the federal poverty threshold was $12,278. For a single-person household, the threshold was $7,929 (Bos et al., 1999).

[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).

Figure 1: New Hope income supplement and child care subsidy



(a) Income supplement



(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 income supplement. 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. For this figure, the child care cost equals 3,600 dollars a year, and it is indicated at the top of the y-axis. The solid line represents the copayment. The subsidy corresponds to the solid area above the copayment line.

the month—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.

In this paper, I focus on two elements of the New Hope package: the income supplement and the child care subsidy. Next, I describe these two components and leave the description of the other components of New Hope for Appendix A.

2.1 The income supplement

Figure 1, panel (a), illustrates the income supplement 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 income supplement complements the EITC subsidy. In the figure, the income supplement is represented as the

[13]The income supplement 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 income supplement in terms of annual benefits, New Hope beneficiaries received their supplements on a monthly basis. The income supplement was not taxable.

difference between the dashed and solid lines—that is, the New Hope subsidy is positive for a worker as long as the New Hope schedule stays above of that of the EITC.[15,16]

To evaluate the economic incentives introduced by the income 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 EITC or New Hope ("No subsidy"), the control group ("EITC"), and treatment group ("New Hope"). Since New Hope requires working 30 hours or more, the New Hope budget set ends at the point of 10 hours of leisure. 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.

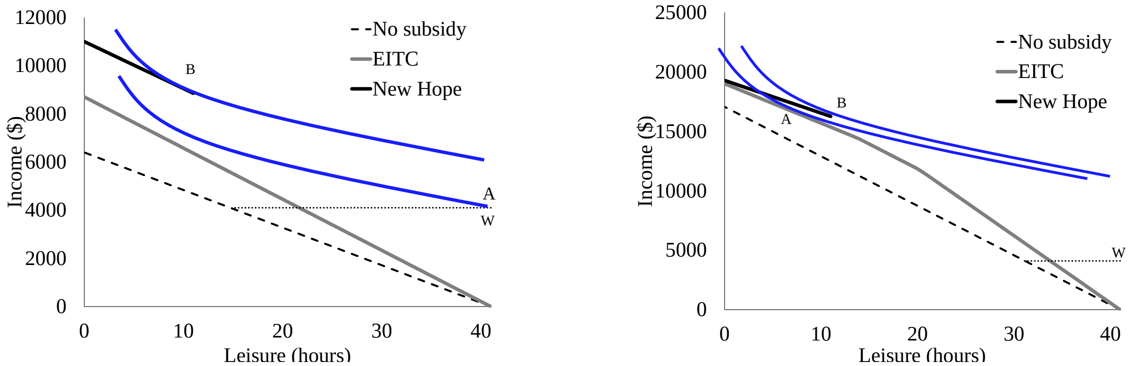
All else constant, the figure indicates that the impact of the program on labor supply depends on the wage offer. Without New Hope (if X and Y were in the control group), individuals would allocate at point A. At this point, the wage offer of X is low enough so that she is better off receiving welfare and not working at all. 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 conterfcatual of

[15]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]Because the income supplement schedule stayed fixed whereas the EITC schedule expanded while the program was running, the treatment "intensity" varied in time. 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 treatment group received lower levels of the income supplement in 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)

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.

not having the program, depending on the relative magnitudes of income and substitution effects. Overall, the New Hope income subsidy should have a non-negative effect on income and an ambiguous effect on hours worked.[18]

Because the income supplement affects parental behavior, it can also produce effects on child outcomes. Suppose that labor supply causes a negative effect on child human capital, while income causes a positive effect (Bernal, 2008; Dahl and Lochner, 2012). Leaving aside the child care subsidy component for a moment, the effect of the program on individual X's child is ambiguous: X has more income but works more. The impact on individual Y's child is also ambiguous. If Y works more, then she would be in the same situation as X: more income but fewer hours at home. If Y works less then we can guarantee a positive effect on children, as the individual spends more time at home and has more income. Therefore, the impact of the New Hope income subsidy on children 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.

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

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. Thanks to the subsidy, families paid a relatively small copayment (shown in the figure as the difference between the solid and dashed lines). 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. 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).[19] 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).[20] 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.[21] Families under New

[19] 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.

[20] 54% of the New Hope full sample were not under AFDC (Bos et al., 1999).

[21] Individuals had to be aware of the different child care assistance programs for which they would be eligible as their situation changed. For example, if a family had left AFDC, then they would have had to apply to a child care for working parents. If they had become unemployed and fell under AFDC again, they

Hope benefited from a simpler system, since New Hope gathered all subsidies into one single program.[22]

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 income supplement 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 care take-up for individual A, her child would benefit from the child care subsidy because A has more income. In contrast, individual B's child would 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 income supplement, theory does not give a clear prediction on the sign of the effect of the child care subsidy on child outcomes.

would have had to redo all paperwork to receive the child care assistance from the public system (Bos et al., 1999; Blau, 2003).

[22]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.

Table 1: Available databases on the New Hope intervention

Data	Variables	Periods
New Hope Survey	Hours worked and child care use and expenditures.	Two, five, and eight years after random assignment.
Teachers' survey	Child outcomes: SSRS Academic Subscale	Two, five, and eight years after random assignment.
New Hope's and Wisconsin's administrative records	New Hope: benefits take-up (income supplement, child care payments). Wisconsin: Labor earnings (UI system), AFDC, and Food Stamps payments.	1994-2003.

Notes: This table shows the available databases (first column), the associated variables (second column), and the years in which they were collected (third column).

3 The data

From August 1994 to December 1995, the MDRC—the agency in charge of the experimental evaluation—recruited the original New Hope sample. This sample consisted of 1,357 individuals; 678 of them were randomly selected to the treatment group and 679 to the control group. To evaluate the intervention's impact, the MDRC collected data on participant's labor market outcomes and families up to eight years after baseline.

Table 1 presents a description of the available databases. The New Hope data consists of three databases: the parents' and children's survey (the "New Hope surveys"), the teachers' survey, and administrative information from the state of Wisconsin. The first database corresponds to the New Hope surveys. These surveys gathered household information on work and child outcomes. In the teacher surveys, teachers gave their assessment on several child academic and behavioral indicators. The administrative records contain information on earnings from the Wisconsin UI system and directly from the firms that hired participants for New Hope's community service jobs.

In my analysis, I exploit data from two samples. Table 2 indicates the number of observations (parents and children) from each sample. As a starting point, I take data on individuals with at least one child at baseline. This 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 (745 adults of the original 1,357).[23] In addition, 50 adults in the CFS database do not match in the youth database, and two children in the youth database do not match in the adult CFS data. I excluded these observations from the analysis, leaving 1,105 children (and 695 parents) as the main baseline CFS sample. For the purpose of structural estimation, I remove applicants with missing data (from years two, five, and eight surveys) ending up with 691 children as the main estimation sample.

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 subsidy in a 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 are 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 316 children out of the 691 children from the estimation sample.

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%), a little more than half are African-American (58% and 53% in the treatment and control group) and 88% do not cohabitate with a spouse or partner. Moreover, only half of the sample has a high school diploma or GED certifica-

[23] 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).

Table 2: Sample size of the Children and Family Study (CFS) across surveys

Data	Treatment	Control	Total
A. Adults			
CFS	344	351	695
Estimation	214	225	439
With young children	133	137	270
B. Children			
CFS	544	561	1105
Estimation	338	353	691
Young children	155	161	316

Notes: This table shows the sample size for different samples for adults (Panel A) and children (Panel B). The first row of each panel presents the number of observations from the the CFS study. The second row shows the number of observations used for estimation (CFS sample after removing missing data). The third row indicates the number of observations for the sample of adults with at least one young child (less than six years of age) by two years after baseline.

tion 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, baseline characteristics do not exhibit economically significant changes and baseline characteristics remain balance (at the 5% level). Finally, for the sample of adults with young children, I do not find statistically significant differences (at the 5% level) in the baseline characteristics between experimental groups (Table B.3).

4 Treatment effects

Bos et al. (1999) and Huston et al. (2001) document experimental evidence on the effects of New Hope on household behavior and child outcomes.[24] Since treatment effects on children were primarily explained by impacts for the sample of young children (Rodriguez, 2018), the focus of this paper is to understand the mechanisms driving the effects on child outcomes for this sample.[25]

[24]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).

[25]Nonetheless, for structural estimation, I use the entire CFS sample (after removing missing observations)

I estimate treatment effects on three household variables—income, labor supply, and child care— and on a measure of child academic skills. To obtain the income variable, I consider labor earnings from the Unemployment Insurance (UI) system, simulated EITC payments, New Hope supplements, community service job (CSJ) earnings, and welfare payments (Food Stamps and AFDC or TANF cash transfers).[26] I define quarterly employment as having a positive UI or CSJ record in a given quarter. Finally, I set the child care dummy as 1 if the child was enrolled in a center-based 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 (that is, she stayed at home with another family member, or attended an informal child care in someone's home). I measure child skills with a ranked-based test score. The measure is an item of the Social Skills Rating System (SSRS), Academic Subscale. I take this variable from the teacher survey. Teachers were asked to rank the child on a discrete-ordered scale according to the child relative academic performance in the classroom. The scale takes five categories, going from "the child belongs to the lowest 10% of the class" to "the child belongs to the top 10% of the class."[27]

Using the public New Hope database and the variables as defined above, Rodriguez (2018) estimates the effect of the program on household choices for families with young children while New Hope was in effect. I compute the effects on household variables from baseline up to three years after the initial period. I find that the program increased household annual income by an average of $900 (a 6% increase), quarterly employment probability by 8 percentage points (from a baseline of 67%), and child care use by 22 percentage points for children under six years of age (from a baseline of 40%).

These changes in household behavior suggest that the program may have influenced child human capital development as well. To assess effects on children, Rodriguez (2018) estimates

to have a bigger sample size.

[26]The income variable does not include other sources of welfare (such as the WIC or the child tax credit) and income from relatives or from other household members. Thus, in my data, it is possible to have participants with zero income.

[27]See Appendix C for a more detailed definition of these variables.

ordered probit regressions where the dependent (observed) dependent variable corresponds to the SSRS measure and the independent variable the random assignment dummy. In these regressions, the unit of observation is a child. I use the sample of children who were six years of age or less by two years after baseline. Since the SSRS measure is available only for children who are old enough to be at school, this sample ($n = 109$) takes children who are mostly 5 or 6 years of age. Using the probit estimates, I simulate the impact of New Hope on scoring "4" or above—which stands for being in the top 30% of the class—on different academic performance measures. Two years after baseline, I find that the program increased the probability of being in the top 30% of the class academic ranking by 16 percentage points from a baseline of 33% (statistically significant at the 5% level). Estimated effects five and eight years after baseline are not statistically significant.[28]

Overall, New Hope had a meaningful impact on household behavior and child outcomes. However, the treatment-effect analysis does not yield precise public-policy implications; as all policies were bundled together we do not have enough sources of exogenous variation to disentangle the importance of each policy in explaining the effects of New Hope.

5 A dynamic-discrete choice model of labor supply, child care, and child's skills

This section presents a dynamic model household choices and child human capital. The model incorporates the economic constraints defined by New Hope, the EITC, and welfare programs as part of the individual's budget set. Shaped by this policy environment, choices of labor supply and child care affect child human capital. Thus, the model is able to shed lights on the household mechanisms by which New Hope impacted child human capital.

The basic timing and features of the model are as follows. At the beginning of time,

[28]The literature finds this fade-out trend in other rank and rank-free measures of academic skills (Huston et al., 2003; Miller et al., 2008). See also Rodriguez (2018) for evidence on the effects of New Hope on young children.

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 old. 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. Each period, the agent makes her choices taking into account 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

$$U(c_t, h_t, \theta_t) = \ln c_t + \alpha^p \mathbf{1}\{h_t = 15\} + \alpha^f \mathbf{1}\{h_t = 40\} + \eta \ln \theta_t, \tag{1}$$

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 is per capita consumption. It represents the average consumption family members enjoy after paying for child care services. α^p and α^f capture the psychic costs or benefits of part-time work, full-time work. θ_t denotes child human capital. Here, parents observe a "true" value of child human capital, that is, an underlying factor that drives academic achievement. 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 the parent that cares for her child's human capital.[29] For married individuals, for all t, the spouse receives no income.[30] All choices are made by the

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

[30] Data on spouse's earnings is available only in New Hope surveys from year two. Among those married or cohabiting (10% of the sample), 44 and 36% of the total income of married respondents in the second-year survey comes from the own participant's and her spouse's earnings, respectively.

caregiver of the child. Having a spouse affects choices by adjusting consumption per-capita (more mouths to feed) and the budget set (welfare rules differ by marriage status).

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

$$\theta_{t+1} = \exp\left(\gamma_0 + \gamma_1 cc_t \mathbf{1}\{a_t \leq 5\}\right) \theta_t^{\gamma_2} c_t^{\gamma_3} \tau_t^{\gamma_4} \tag{2}$$

where cc_t is a child care dummy—equal to 1 for center-based child care and 0 for home care or any informal care at someone's home—and τ_t are weekly hours the individual spends with the child. The indicator function next to the child care dummy implies that only an individual with a young child (age $a_t \leq 5$) can use the child care option. The coefficients γ_k, for $k = 1, \ldots, 4$, represent the effect of current-period inputs on next-period child human capital. The constant in the production function (γ_0) is normalized so that $E[\ln \theta_t] = 0$ for $t > 0$. γ_1 is a total factor productivity (TFP) parameter. It captures the human capital gain from center-based child care relative to home care.

Equations (1) and (2) imply that per-capita consumption enters individual's utility both directly and indirectly through the production function. 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 utility (equation 1) or the process of human capital formation (equation 2). Having more children influences choices only through per-capita consumption and the budget set; an additional child in the household, all else equal, lowers c_t and changes the eligibility for 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.[31]

[31] 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

Wages. Each period, the individual draws a value of 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 also depends on an individual productivity that follows an AR(1) process. Formally, the wage offer process is given by

$$\begin{aligned} \ln w_t &= X_t^{w\prime} \beta^w + \nu_t^w, \\ \nu_t^w &= \rho \nu_{t-1}^w + \epsilon_t^w \\ \epsilon_t^w &\sim N(0, \sigma_w^2) \end{aligned} \tag{3}$$

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

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.

Budget set. The budget set incorporates various features of the welfare system. Income is a function of labor supply, earned income, and various mean-tested programs. Conditional on eligibility, the agent receives payments from New Hope, the EITC, the AFDC or Food Stamps.[32] Eligibility to these programs and payment amounts depend on working hours, earned income, and family composition.

Income can be represented as follows. 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

families with more than two children (Bernal, 2008; Del Boca et al., 2013), implying losing more than 50% of the sample.

[32]New Hope administrative data does not include other forms of welfare payments.

and 0 otherwise). Income (I_t) is given by

$$
\begin{aligned}
I_t = {} & w_t h_t \times 52 + EITC_t(w_t h_t \times 52, k_t, m_t) + NH_t(w_t h_t \times 52, k_t, m_t) \\
& + B_t + S_t. \qquad (4)
\end{aligned}
$$

In the equation above, $EITC_t(.)$ corresponds to EITC payments. If the individual is eligible to receive these payments, she always comply.[33] 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, the individual always takes up the benefits of AFDC and Food Stamps payments (Blundell et al., 2016).[34] 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 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:

$$
\begin{aligned}
B_t &\equiv \rho_t^B B_t^*(w_t h_t \times 52, k_t, m_t), \\
S_t &\equiv \rho_t^S S_t^*(w_t h_t \times 52, k_t, m_t),
\end{aligned}
$$

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 function of the level of earn-

[33] 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%.

[34] 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.

ings, labor supply, and family composition (k_t and m_t). These rules may change from year to year.[35] Nonetheless, at $t = 0$, 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.[36] Moreover, eligibility rules are always enforced, including the New Hope work requirement.[37]

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 ($t = 2$), the wage of the state-provided CSJ is part of the pool of potential log-wage offers (equation 3). Participants do not face time limits for W-2.[38]

Per-capita consumption. Consumption is defined as money net from child care expenditures. Agents have access to child care services at a fixed, known price p for all t. This price corresponds to the expected price in a market where free and private child care coexist. If the agent is in the New Hope treatment group and works full time, she gets a lower copayment, $\underline{p} \leq p$, which depends on the level of earnings (see Section 2). Formally, the cost function equals:

$$\delta(p, D, h_t) \equiv \begin{cases} \underline{p}\mathbf{1}\{h_t = 40\} + p\mathbf{1}\{h_t < 40\} & \text{if } D = 1, \\ p & \text{otherwise.} \end{cases} \tag{5}$$

The individual cannot save or borrow.[39] Per-capita consumption is thus given by:

[35] See Appendix D for details.

[36] 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).

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

[38] The model's version of W-2 does not include time limits because it would require having data on labor supply beyond 2003.

[39] There is little evidence suggesting that individuals are able to save for future consumption. In the control group, from the year-five interview, 58% manifested some concern about not having enough money

$$c_t = \frac{I_t - cc_t \times \delta(p, D, h_t)}{1 + m_t + k_t}. \tag{6}$$

Parental time. Time with the child (τ_t) is defined by labor supply and child care choices. As children enter school, they cannot access child care services and total available time to spend with parents is automatically reduced. Let $\overline{T}$ be the total available time the adult has in a week and $\widetilde{T} < \overline{T}$ the time a school-age child spends at school. τ_t is defined as

$$\tau_t \equiv \begin{cases} cc_t(\overline{T} - 40) + (1 - cc_t)\left(\overline{T} - h_t\right) & \text{if } a_t \leq 5 \\ (\overline{T} - \widetilde{T}) - h_t & \text{otherwise.} \end{cases} \tag{7}$$

The logic behind equation (7) 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. 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 must spend 20 hours a week away from home, so $\tau_t = \overline{T} - 20$. Analogously, $\tau_t = \overline{T} - 40$ if she works full time. If the child spends her time in child care ($cc_t = 1$), then she 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 $\overline{T} = 168$ (24 hours, seven days a week) and $\widetilde{T} = 35$, available time for school-age children is $\overline{T} - \widetilde{T} = 133$ hours on a week.[40]

Equations (1), (2), and (7) determine the benefits and costs the agent faces when choosing labor supply and child care. Child care allows the individual working more and thus having more income without reducing child human capital (if $\gamma_4 > 0$ in equation 2). Thus, she can consume more (equation 1) and have more income to produce further child human capital. At the same time, child care has a direct, positive effect on child human capital (if $\gamma_1 > 0$ in

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.

[40]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.

equation 2). Hence, the benefits of child care are twofold: it directly produces child human capital and it lowers the cost of labor supply.

Parental leisure and time spent with the child have the same effect on utility. Following equations (2) and (7), any time allocated outside the labor market (if the child is at home) has a constant effect on human capital.[41] Moreover, given the 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.

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:

$$m_{t+1}^* = f_m(X_t^m, m_t), \tag{8}$$

$$k_{t+1}^* = f_k(X_t^k, k_t, m_t), \tag{9}$$

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_t^m includes a constant and age of the adult. X_t^k includes a constant, age, and age squared of the adult.

The dynamic problem. In each period, given a set of state variables, the individual solves a dynamic problem of labor supply and child care choices. The state variables of the problem are collected 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 $\boldsymbol{X}$ contains the wage offer, marriage, and childbearing processes control variables, $\boldsymbol{X} \equiv \left(X^w, X^m, X^k\right)$, and the misinformation shocks to welfare take-up, $\boldsymbol{\rho}_t \equiv \left(\rho_t^B, \rho_t^S\right)$. For a given $\boldsymbol{s}_t$, each period the

[41] Because New Hope data does not have time diaries, I cannot distinguish between passive or active time with the child (Del Boca et al., 2013; Brilli, 2014). Nonetheless, the literature consistently shows that non-working mothers do spend more time with their children than working mothers (Guryan et al., 2008).

agent maximizes the present discounted value of the utility stream by choosing labor supply and child care type. Let $\mathcal{C} = \{0, 1\}$ and $\mathcal{H} = \{0, 15, 40\}$ 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 ($a_t > 5$).

Because agents have different associated initial values of child'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.

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 individual is represented in the usual recursive formula

$$\begin{aligned}
V_t(\boldsymbol{s}_t) &= \max_{j \in \mathcal{J}(a_t)} \{V_t^j(\boldsymbol{s}_t)\} \quad \text{subject to (1)-(9)}, \\
V_t^j(\boldsymbol{s}_t) &= u(\boldsymbol{s}_t, j) + \beta E[V_{t+1}(\boldsymbol{s}_{t+1}) \mid \boldsymbol{s}_t, j] \qquad t < T(a_0).
\end{aligned}$$

The model is closed with initial and terminal conditions. At baseline ($t = 0$), individuals have associated fixed values defining family composition (m_0, k_0) and child age (a_0) and draw an initial value for child human capital θ_0. The initial θ_0 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

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

6 Identification and estimation

6.1 Identification

To reduce the dependence on distributional and functional form assumptions, the policy environment within the model offers various sources of exogenous variation. These shocks are the TANF implementation and expansions of the EITC schedule. Moreover, cash transfers from TANF or AFDC depend on family structure (number of children and marriage status). Furthermore, there are several discontinuity points in the rules of the different mean-tested programs. All of these policy shocks within the model affect labor supply and child care decisions without directly changing preferences, the wage offer equation, or the production function. Therefore, global identification hinges on the comparison of family 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.[42]

I use observed data on inputs and the SSRS measure of overall academic achievement to identify the production function (equation 2). The econometrician observes a noisy measure (M_t) of child human capital. It is a ordinal measure that is given by

$$M_t = \begin{cases} 1 & \text{if } \ln\theta_t + \epsilon^z_{t,m} \leq \kappa_{1,t} \\ 2 & \text{if } \kappa_{1,t} < \ln\theta_t + \epsilon^z_t \leq \kappa_{2,t} \\ \vdots & \qquad \vdots \\ 5 & \text{if } \ln\theta_t + \epsilon^z_t > \kappa_{4,t}, \end{cases} \tag{10}$$

where θ_t is observed by the families but not by the econometrician and ϵ^z_t is measurement error that follows a known distribution. A key identifying assumption is that the production

[42] In Appendix F, 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.

function is constant in time and it does not vary by age (except in the child care component). Observing human capital measures for different samples at different points in time helps to identify the production function and the structure of the measurement system. Appendix E provides the formal identification argument. Intuitively, identification follows in two steps. First, one can show identification of the technology of young children at home care with data on inputs (consumption and hours at home) and one measure of human capital observed for two periods. This result follows because the production function does not vary by period. Once the technology for a young child at home is identified, we can use the fact that cutoffs ($\kappa_{j,t}$, for $j = 1, 2, 3, 4$) are constant across child age and child care types to identify the TFP parameter.[43]

All cutoffs $\kappa_{j,t}$, can vary in time. The assumption of time-varying cutoffs restricts the family of productions functions that can be estimated. In particular, this assumption implies that the constant term in the production function (equation 2) cannot vary freely.[44]

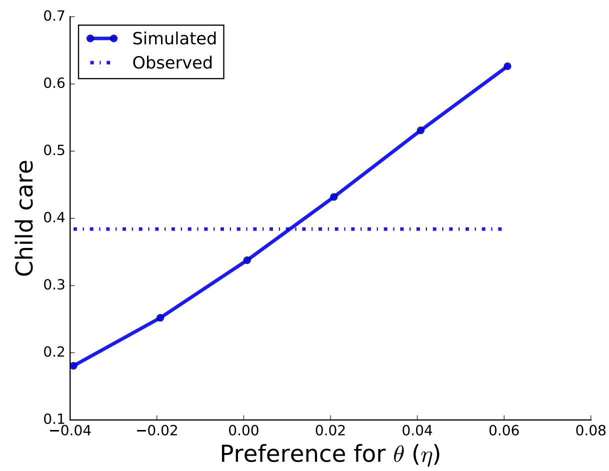
Some non-experimental moments contain identifying information at the local level. Around a vicinity of the true value of a structural parameter, and holding the rest of parameters constant, there is only one value of the parameter that generates the sample moment. To illustrate the sources in the data that contribute to the identification of the structural parameters, Figure 3 plots the relationship between a simulated moment and a structural parameter, holding the rest of the parameters fixed.[45] In this case, I plot the preference for human capital (η in equation 1) and the proportion in the sample who use child care. A higher preference for θ means that the agent is willing to sacrifice more consumption for

[43]Factor loadings—the coefficient associated with $\ln \theta_t$—equal 1 for every period. This assumption is necessary for identification, given that there are no baseline measures of child human capital. By assuming factor loadings are known, the requirement of having multiple measures at baseline is no longer needed. A byproduct of this assumption is that I only need one measure per period to identify the production function. Furthermore, I do not need to impose the requirement that the coefficients of the production function sum up to one. See Agostinelli and Wiswall (2016) for the necessary conditions to identify a production function with an unknown scale.

[44]Only with constant cutoffs across time (or that follow a predictable pattern), one would be able to identify γ_0 as a free parameter and thus let the production function have a time-varying TFP (Agostinelli and Wiswall, 2016).

[45]Voena (2015) and Autor et al. (2017) follow the same approach to show local identification.

Figure 3: Local identification of the preference for human capital



Notes: The figure plots the proportion of children in child care from the model against the structural parameter of preference for human capital (solid line). This parameter is locally identified at the crossing point with the corresponding observed moment (depicted in the dotted line).

higher levels of child human capital. Thus, for a given child care cost and holding other parameters fixed at their estimated values, a bigger η implies a larger probability of choosing center-based child care. The simulated probability of child care increases monotonically, crossing the observed value in the data only once. Hence, at this crossing point, η is "locally identified." In this way, the chosen moment contains sufficient identification power at the local level—around a vicinity of the optimal parameter value, holding other parameters constant—to pin down the structural parameter. As I explain next section, to exploit these sources of identification, I use this and other moments that meet the single-crossing property directly in the estimation procedure.

6.2 Estimation

For estimation purposes, I 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 of moments.[46]

[46]This two-step procedure is a standard practice in the literature. For instance, see Gourinchas and Parker (2002), De Nardi et al. (2010), Voena (2015), and Blundell et al. (2016). The goal with the two-step

External estimation and calibration. Table 3 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}), consider the following linear probability models:

$$m_{t+1} \quad = \quad X^m_t \beta^m + m_t \gamma^m + \epsilon^m_{t+1}, \tag{11}$$

$$k_{t+1} - k_t = X^k_t \beta^k + k_t \gamma^k + m_t \gamma^{k,m} + \epsilon^k_{t+t}. \tag{12}$$

Since I do not have marriage data for two years in a row, I cannot directly estimate the parameters of equations (11) and (12). To circumvent this problem, I estimate a linear probability model of m_{t+1} on m_{t-1} and X^m_{t-1}, and use the resulting reduced-form parameters to identify β^m and γ^m.[47] I implement a similar method to identify β^k, γ^k, and $\gamma^{k,m}$.[48] Given the estimated parameters of equations (11) and (12), the parameters of the binomial distribution determining the probabilities of marriage and childbearing (equations 8 and 9) are given by $m^*_{t+1} = X^m_t \widehat{\beta}^m + m_t \widehat{\gamma}^m$ and $k^*_{t+1} = X^k_t \widehat{\beta}^k + k_t \widehat{\gamma}^k + m_t \widehat{\gamma}^{k,m}$.

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 (\$750 a month) and weight it by the proportion of control-group children who are not in Head Start (0.43 × \$750). 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).

procedure is to keep estimation computationally feasible.

[47] To estimate this regression, I use data for the second-year survey and baseline information.

[48] Precisely because I do not have data for two periods in a row, I was unable to implement a logistic form to estimate the marriage and childbearing processes.

Table 3: 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)	\$323 monthly
Take-up probabilities of AFDC and SNAP	Average AFDC and SNAP take-up conditional on eligibility	0.6 and 0.7

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 compares the estimated moments of an auxiliary model using observed data on choices and exogenous variables with equivalent estimates from the model-simulated data (Gourieroux et al., 1993).

I use backward induction to solve the model and obtain paths of simulated choices. Because $\boldsymbol{s}_t$ contains continuous variables, obtaining an exact solution for $V_t(\boldsymbol{s}_t)$ at every point of the state space is computationally unfeasible. Thus, following Keane and Wolpin (1994) and Keane et al. (2011), 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. The grid has 648 observations. Finally, I use Monte Carlo integration (with 50 draws) to estimate the multivariate integral.[49]

The estimation problem can be stated as follows. Let $\hat{g}$ be the vector of moments extracted from the data. I solve the model $M = 1,000$ times for a sample size of $n = 691$ children and compute the required moments from simulated data. Let $\{\boldsymbol{\epsilon}^m_t\}^M_{m=1}$ denote the structural random shocks (fixed across the estimation procedure). Let ψ be the vector of structural parameters of the model. Define $\{y^m_{it}(\psi)\}^M_{m=1}$ as the simulated choices associated with the M draws of structural random shocks. Let $\hat{g}^m(\psi)$ be the equivalent moment

[49] I set the grid size and the number of draws for the Monte Carlo integration in order to balance precision and computational time.

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 $\hat{g}$ 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). I use the bootstrap method (1,000 samples) to estimate W. I 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. Based on the argument given in Section 6.1 (see Figure 3), estimation targets moments that provide identification at the local level.[50] 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 7) with the probability of scoring 4 or 5 in the SSRS overall assessment. To estimate the measurement system, I include various moments capturing the distribution of children in the SSRS rankings from two and five years after random assignment.[51] Finally, to estimate the wage offer process, the auxiliary model includes the OLS coefficients of a regression of log wages onto the variables discussed in the context of equation (3). Appendix G shows that the model successfully matches all target moments.

[50]Appendix G describes how I construct the main variables of the model combining administrative and survey data to compute target moments for estimation. Appendix G shows that each of the chosen moments locally identifies a structural parameter.

[51]I use the "overall" SSRS measure. This variable shows the reported rankings based on the overall academic performance of the child in a classroom. In a PCA analysis using all of the SSRS measures, the overall test score has the highest correlation with the first PCA component in years two and five.

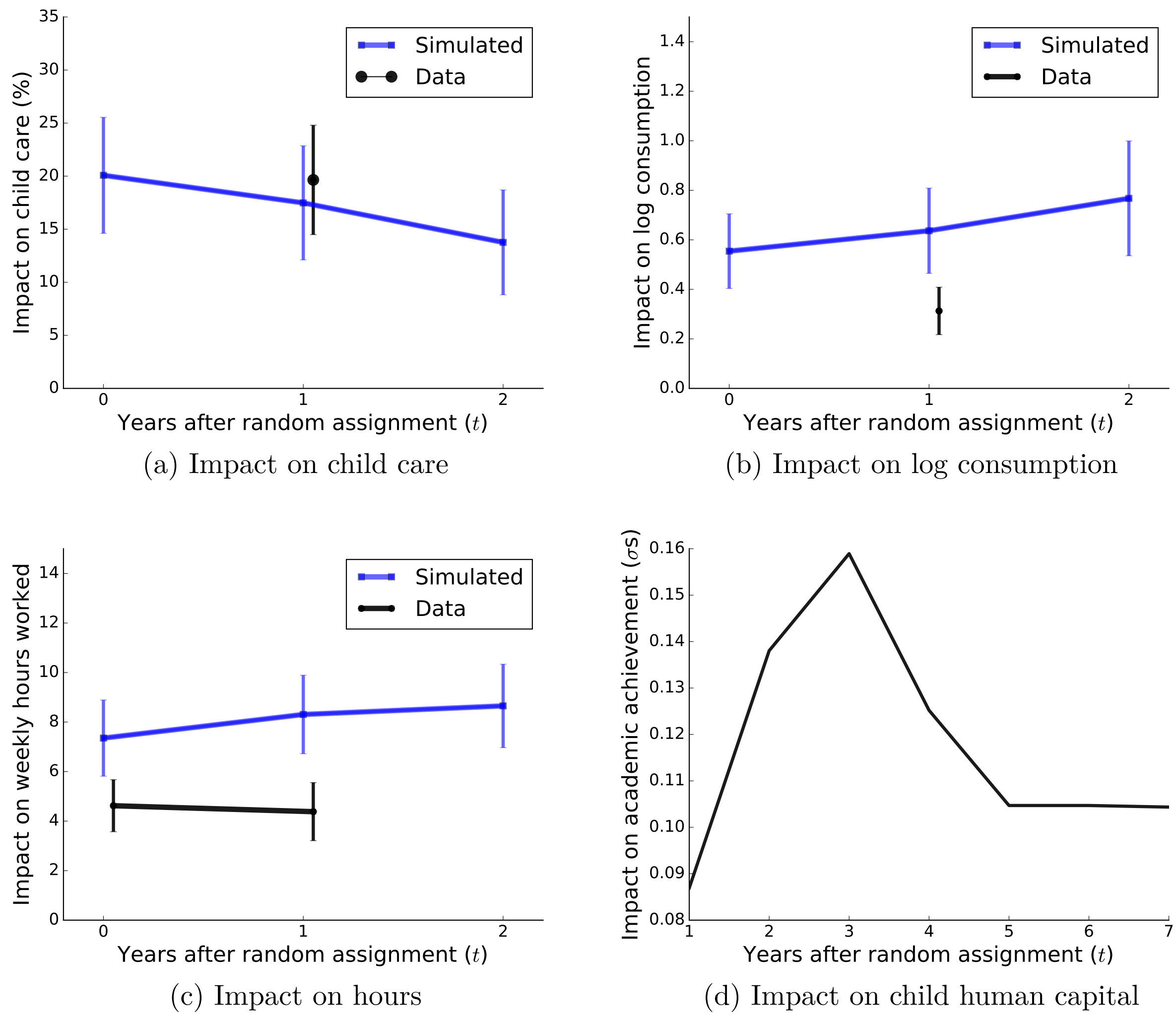
Validation. Before presenting the counterfactual experiments, I analyze the model's capacity to predict non-targeted moments. These moments (that were not used in estimation) exploit the experimental variation induced by the New Hope random assignment. This form of validation is rarely used in the structural literature on child outcomes and household behavior (Bernal, 2008; Del Boca et al., 2013).

Figure 4, 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. I show results for the sample with children under six years of age by $t = 2$. In those periods where I am able to compute treatment effects with the actual data, the model predicts a higher impact on hours worked (eight hours a week in the model versus fours hours in the data), an almost equivalent impact on child care (20 percentage points in the data versus 18 percentage points in the model), and a higher impact on log per capita consumption (0.6 log-consumption units in the model versus 0.3 in the data).

The lack of predictive power in some of the experimental moments should not affect overall conclusions. The impact of New Hope on child human capital (as I show next) is mostly explained by the child care component. On the one hand, in terms of the production of human capital, income plays a minor role. This result is explained because the productivity parameters of income is relatively small (see the discussion in the following section). Hence, the upward bias in predicting the effects of New Hope on income is heavily discounted in the production function. On the other hand, the fact that my model overshoots the employment effects, but still predicts that child care as the most influential input in New Hope's effects, only reinforce the main qualitative conclusions of this paper.

Panel (d) of Figure 4 computes the model-predicted impact on early childhood human capital. In line with previous evidence (Huston et al., 2001, 2005, 2011), the impact of New Hope on child human capital is positive and increasing while New Hope was in effect, and decreases thereafter. By $t = 3$, the effect on child human capital reaches a maximum of 0.16 standard deviations units and decreasing thereafter. This impact is equivalent to an increase

Figure 4: Simulated and observed treatment effects



Notes: Panels (a)-(c) compare the simulated and observed treatment effects on household variables. Panel (d) depicts the simulated impact on child human capital. Arrows indicate the associated simulated impact on the probability on being in the top 30% according to the SSRS measure

of about six percentage points in the probability of being in the top 30% of the academic achievement distribution. Hence, even though the model predicts similar patterns in the effects on child human capital, the magnitudes are lower than those of the data.

7 Model estimates and implications for household behavior and child human capital

7.1 Estimation results

Table 4 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 691 children and of their principal caregivers.[52]

Panel A presents the parameters of the utility function (equation 1). Since utility is expressed in log-consumption units, taste parameters represent what the agent is willing to pay (in terms of a percentage change in current-period consumption) to compensate for a marginal increase in one input while keeping the others fixed. Child human capital is positively valued by the agent: the individual is willing to sacrifice 1% (= 0.01/1, where 1 is the estimated standard deviation of $\ln \theta_t$) of consumption for a one-standard-deviation increase in child human capital.[53] Consistent with the literature (Meghir and Phillips, 2010; Blundell et al., 2016), the implied (marshallian) extensive-margin elasticity is larger than the (marshallian) intensive-margin elasticity (0.54 versus 0.14).

Panel B shows the estimated parameters of the wage offer process (equation 3). The positive coefficient associated to the trend variable implies that the wage offer increases for everyone, capturing a growing labor demand.[54] A high school diploma increases the wage offer by 24%. This estimate is higher than the return to high school graduation of 10% for men estimated by Heckman et al. (2016a,b). The variance of the wage process (0.28)

[52] 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.

[53] Here, the literature provides a wide range of estimates: Bernal (2008) estimates an almost 0 coefficient, while Del Boca et al. (2013) documents that a one-percent increase in child human capital is more valued than the same increase in consumption.

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

Table 4: Estimated structural parameters

Parameter	Estimate	S.E.
A. Utility function		
Preference for part-time work (α^p)	-0.029	0.061
Preference for full-time work (α^f)	-0.820	0.070
Preference for human capital (η)	0.011	0.001
B. Wage offer		
High school dummy	0.238	0.002
Trend	0.085	0.001
Constant	1.488	0.020
Variance of error term	0.281	0.000
AR(1) error term	0.622	0.006
C. Production function		
Child care TFP (γ_1)	0.607	0.021
Lagged human capital (γ_2)	1.103	0.002
Consumption (γ_3)	0.017	0.002
Time at home (γ_4)	0.930	0.052
$Corr(\varepsilon_0^\theta, \varepsilon_0^w)$	-0.209	0.007
D. SSRS ($t = 2$)		
κ_1	-1.717	0.034
κ_2	-0.615	0.031
κ_3	0.962	0.010
κ_4	2.192	0.011
E. SSRS ($t = 5$)		
κ_1	-1.639	0.080
κ_2	-0.076	0.078
κ_3	1.479	0.085
κ_4	3.096	0.126

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 $\ln w_t = X_t^{w\prime}\beta^w + \epsilon_t^w$, 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 $\theta_{t+1} = \exp\left(\gamma_0 + \gamma_1 cc_t \mathbf{1}\{a_t \leq 6\}\right) \theta_t^{\gamma_2} c_t^{\gamma_3} \tau_t^{\gamma_4}$.

is bigger and the autocorrelation coefficient of the unobserved component of the wage offer (0.62) is lower compared to what Blundell et al. (2016) find for women without a high school diploma. Hence, relative to the Blundell et al. sample, New Hope participants face a larger degree of uncertainty regarding future wage shocks.

I show the estimated parameters of the production function and measurement system in Panels C-E. Consumption has a positive but small effect on human capital. Assuming no behavioral responses and holding constant labor supply, a 1,000-dollar boost in one period rises child human capital by 0.3% of a standard deviation the next period. This effect is smaller than what is reported in Dahl and Lochner (2012) and Dahl and Lochner (2016).[55] Nonetheless, the experiments are not comparable. Section 8.3 includes the fact that money can be used to purchase child care services as well, finding that the reduced-form effects of the EITC on child human capital of this paper are similar to those of Dahl and Lochner (2012).

Time at home has a positive effect on children's human capital. Conducting a similar experiment as the paragraph above, I compute the effect of going from $h_t = 40$ to $h_t = 0$ (*ceteris paribus*), assuming no one uses child care. This labor supply change rises child human capital by 25% of a standard deviation, in line with studies showing economically meaningful impacts of parental time (Cunha et al., 2010; Del Boca et al., 2013; Attanasio et al., 2015).

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 52% of a standard deviation. Instead, if the same money for buying child care services is used for consumption, child human capital increases by only 0.8% of a standard deviation. Large effects of child care on participant children, with similar magnitudes, have been also found in the Head Start literature (Feller et al., 2016; Kline and Walters, 2016).

The estimates indicate that 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 almost permanent consequences for skills production in the future. This feature of the human capital technology has important implications for predicting the effects of policies such as the EITC on child human capital in the long run.

[55] Bernal (2008) and Del Boca et al. (2013) also find that money plays a modest role in explaining child cognitive outcomes.

7.2 Mediation analysis

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.[56] 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

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

where each term on the right-hand side identifies the contribution of the corresponding input in explaining the effect of the program.[57]

I compute the above decomposition using the structure of my model.[58] For period $t = 1$, child care explains most of the effect of the program (120%), while income and labor supply explain a smaller proportion (10% and −30%). Therefore, the negative effect produced by the rise in labor supply is more than compensated by the positive effects from the increase

[56] 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).

[57] 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.

[58] Appendix H document the results graphically.

in child care use and income. This interaction explains the positive impact of New Hope on child human capital in period $t = 1$.

The effect of New Hope on child human capital becomes larger once we consider the dynamic of human capital accumulation in the long run. In period $t = 2$, the contribution of income and child care to the effect of New Hope on human capital equals 0.6% and 7% of a standard deviation of human capital, respectively. Furthermore, given the autoregressive coefficient in the production function, a large share of the human capital acquired in period $t = 1$ remains for period $t = 2$. Thus, human capital accumulation in $t = 2$ is mostly explained by the human capital gain from the previous period (68%). These forms of additional "investment"—more money, child care use, and current human capital stock—make the effect of the program on child human capital larger in $t = 2$ than in $t = 1$. Therefore, as the program induces changes in behavior leading to further increases in child human capital, the program's impact on child human capital grows over time.

8 Understanding the effects of New Hope

8.1 Income and child care subsidies

In this section, I study which components in the New Hope package 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 academic skills. The goal is to evaluate the effect that income and child care subsidies have on child human capital.[59] I leave the analysis on work requirements and child human capital for next section.

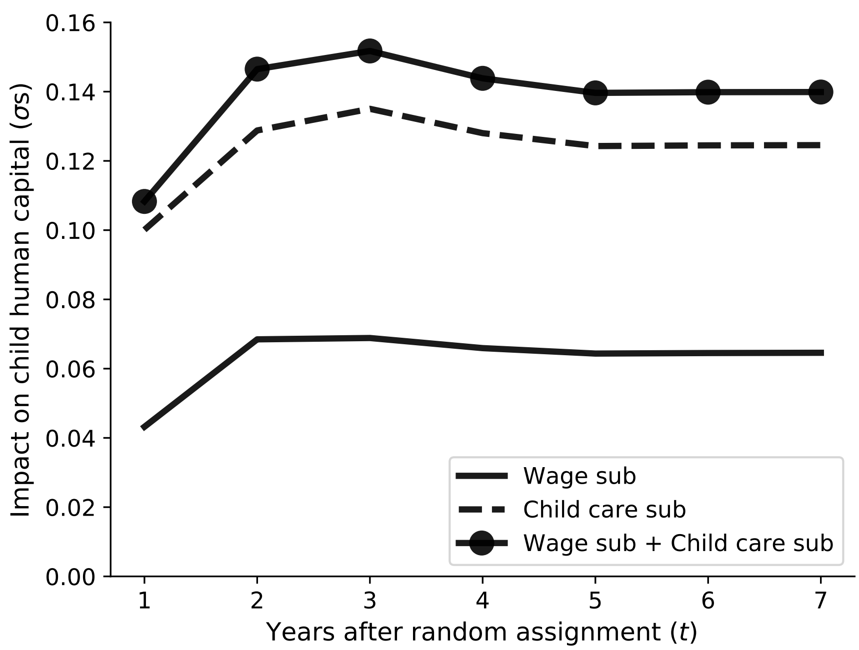
I compute the effects of different New Hope policies on children and the family. In these experiments, I change the parameters of the New Hope package and re-compute treatment

[59] Grogger and Karoly (2009) review the impacts of a series of welfare experiments on children human capital. They suggest that the varied results coming from these experiments may be explained by the different types of policies that each program included.

effects on household behavior and child outcomes under different versions of New Hope. In every policy combination, I assume that work requirements are not in place. As with previous analyses, I focus on the sample of children who were six years of age in period $t = 2$.

Figure 5 presents the effect of New Hope alternative policies on child human capital. It reveals that New Hope's effect on child human capital is mostly explained by the child care subsidy. We can see this result by comparing a policy that includes only a child care subsidy versus a policy that only has a wage subsidy. The figure shows that the effect of the child care subsidy on child human capital is larger than that of the wage subsidy: on average, the impact on child human capital of the child care subsidy (0.12 standard deviations) is 97% bigger.

Figure 5: Effects of income and child care subsidies on child human capital



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.

Table 5 presents the average treatment effect on household choices. In each row, the table depicts the effect of a particular policy (in columns) on average labor supply, child care use, and consumption per capita from $t = 0$ to $t = 2$. The wage subsidy has larger effects on income and employment than the child care subsidy: the wage subsidy increases employment and consumption by 15 percentage points and 842 dollars, while the child care subsidy has almost a null effect on employment and raises consumption by 332 dollars. In contrast, the impact on child care use is bigger for the child care subsidy (13 percentage points) than for the wage subsidy (7 percentage points). Since, for the same money, child human capital increases more from buying child care services instead of consumption, the larger impact on child care use of a child care subsidy implies that this policy generates more child human capital than a wage subsidy. In any case, for both policies, most of the impact on child human capital can be accounted by the increase in child care use. In fact, for period $t = 1$, the increase on child care use of period $t = 0$ explains almost 100% of the impact of these two counterfactual policies on child human capital (see Appendix H).

Table 5: The effects income and child care subsidies on household choices

ATE	(1)	(2)	(3)
Consumption (US$)	842	332	1316
Part-time	0.190	0.071	0.205
Full-time	-0.038	-0.079	-0.082
Child care	0.065	0.132	0.144
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 $t = 2$. To estimate impacts, I take averages of annual effects from $t = 0$ to $t = 2$. Each policy (indicated with "✓") is compared to a counterfactual scenario where no policy is implemented.

The counterfactual experiments shed lights on the potential complementarities arising from putting wage and child care subsidies together.[60] Note that the actual "effect" on child

[60] The bulk of the literature evaluating welfare reforms does not consider that combined policies may not be equal to the reported effects of different policies from different studies. See for example Moffitt (2003) and Moffitt (2016).

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 is already in place. The effect on child human capital of this policy averages 0.08 standard deviations. In contrast, implementing the child care subsidy when no policy is in place boosts child human capital by 0.12 standard deviations. This result is mainly explained because the impact on child care use is lower in a policy that introduces a child care on top of a wage subsidy (an eight-percentage points increase) relative to the scenario where neither policy is in place (a 13-percentage points increase).

Overall, results from this section are in line with current research on the effects of child care subsidies on the family (Baker et al., 2008; Herbst and Tekin, 2010a,b; Havnes and Mogstad, 2011, 2015; Black et al., 2014; Cornelissen et al., 2017). An emerging 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., 2017). My model predicts that similar, large effects are explained given a large the productivity gap of child care relative to home care. My counterfactual analysis indicates that once low-income families have access to affordable child care, average effects on children can emulate economically meaningful effects that are found for high-quality early childhood interventions (Gross et al., 1997; Campbell et al., 2002; Heckman et al., 2010; Gertler et al., 2014) and Head Start (Kline and Walters, 2016; Feller et al., 2016).

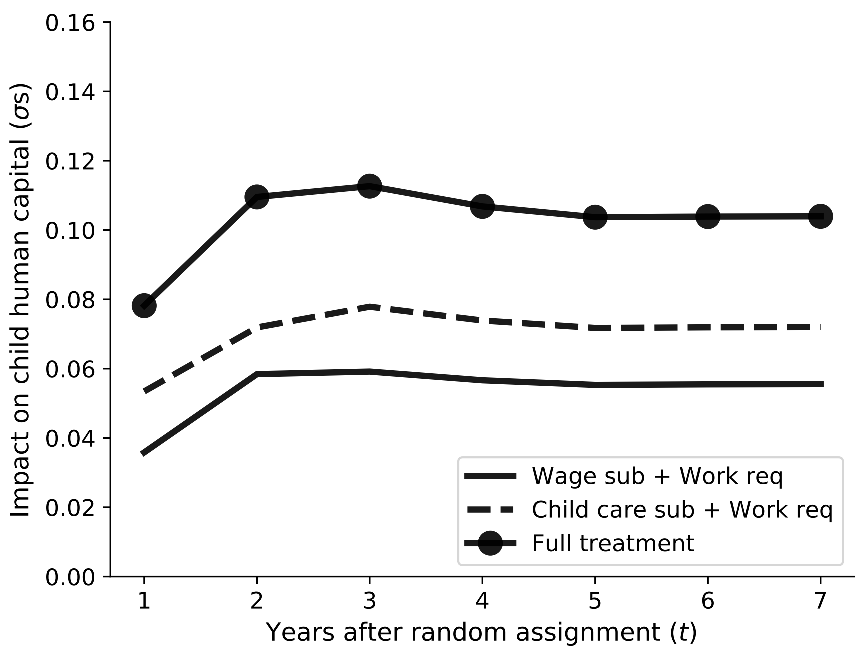
8.2 Work requirements and child human capital

Last exercise assumed that a full-time work requirement was not needed to have access to New Hope benefits. In this section, I add a work requirement into the analysis and study the consequences for household behavior and child human capital.

Figure 6 plots the effects of different policy combinations on child human capital, where all of these policies include a work requirement. The New Hope work requirement causes a negative effect on child human capital. Compared to policies without work requirements

(Figure 5), the effects on child human of policies with the work requirement capital are lower. Combined with the work requirement, the child care subsidy increases child human capital by 0.07 standard deviations on average, 58% of what the child care subsidy by itself does. A wage subsidy with a work requirement increases child human capital by 0.05 standard deviations, or 87% of the effect of the policy without a work requirement. Taking both policies together, if New Hope had not included a work requirement, the impact on child human capital would have been 40% bigger (0.04 standard deviations). These results provide novel evidence to the research studying the impacts of work requirements (Grogger, 2003; Chan, 2013).[61]

Figure 6: Effects of income and child care subsidies under work requirements on child human capital



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.

Table 6 shows the effects of policies with work requirements on household behavior. The

[61]In addition, many welfare experiments similar to New Hop incorporated work requirements (Grogger and Karoly, 2009). However, reaching a solid conclusion have proven to be difficult as the impact of the work requirement has not been experimentally tested in isolation.

table suggests that the smaller impact of the policies subjected to a work requirement are explained by a larger effect on full-time employment and a lower impact on child care use. In line with this result, Appendix H reveals that the contribution of the increase in child care use to the overall effect on child human capital is lower in policies including work requirements. Thus, for the most part, the lower effect on child care use explains why a work requirement can be detrimental to the accumulation of child human capital. The resulting lower child care impact of the bundled policy suggest that, for a group of participants, the child care option is valuable only if they are not required to work full time to get the subsidy.

Table 6: The effects income and child care subsidies under work requirements on household choices

ATE	(1)	(2)	(3)
Consumption (US$)	894	552	1569
Part-time	-0.072	-0.064	-0.114
Full-time	0.166	0.120	0.239
Child care	0.056	0.068	0.100
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 $t = 2$. To estimate impacts, I take averages of annual effects from $t = 0$ to $t = 2$. Each policy (indicated with "✓") is compared to a counterfactual scenario where no policy is implemented.

Even though the work requirement may be detrimental to child human capital, the policy could be used nevertheless as a tool to promote work. Thus, from a social welfare point of view, a work requirement might still be desirably if the increase in adult's welfare (if any) more than compensates the reduction on children´s welfare (which might be a function of child human capital). Yet, as the counterfactual experiments suggest, the work requirement does not have major effects on employment and income. The work requirement makes the wage subsidy less attractive for a sample of individuals who would prefer staying out of the labor market but would work part-time under a program without the work requirement.

The wage subsidy policy alone boosts employment by 15 percentage points, whereas the wage subsidy tied to the work requirement increases employment by 9 percentage points. Moreover, relative to the wage subsidy without the work requirement, both policies increase the effect on consumption by only 52 dollars.

The mild effects of the work requirements on labor supply and income 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.

8.3 The EITC

My production function estimates imply that the productivity of money is relatively small. This result might seem odd considering results from the literature that leverages EITC-induced variation in income. This line of research shows sizable effect of income on child outcomes (Dahl and Lochner, 2012; Maxfield, 2013; Hoynes et al., 2015; Manoli and Turner, 2015; Bastian and Michelmore, 2017). In this section, I study this apparent contradiction and argue that results can be reconciled once we acknowledge the dynamics implied in the production function.

By using the model's structure and modifying policy parameters, I estimate the effects of the EITC on child human capital. In this experiment, the treatment consists of having the EITC or a child care subsidy (or both).[62] In period $t = 0$, the individual receives an unexpected policy change. The agent knows exactly how the policy parameters evolve for the rest of the periods. In contrast to New Hope, the EITC and child care subsidy are permanent policies.[63] As with the previous simulations, this experiment uses the sample of

[62]Instead of calibrating the actual parameters of the child care subsidy implemented in Wisconsin ("Wisconsin Shares"), I expand the policy implemented in New Hope for all years. Wisconsin Shares followed a similar structure to that of New Hope (Bos et al., 1999). These experiments assume that the individual must work at least part-time to have the subsidy.

[63]In this model, I am silent about the labor supply effects for married individuals coming from intra-household responses to spouse's income. In this regard, Eissa and Hoynes (2004) find that the EITC has a negative effect on married women's labor force participation, but the impact is relatively small. Moreover, approximately 90% of the women in my sample are single at baseline.

Table 7: The effect of the EITC and a child care subsidy

Variable	(1)	(2)	(3)
Consumption (US$ 1,000)	0.11	0.04	0.17
Part-time (percentage points)	2.02	2.94	4.92
Full-time (percentage points)	-0.15	-0.23	-0.78
Child care (percentage points)	5.39	11.91	14.59
EITC (1995-2003)	✓		✓
Child care subsidy		✓	✓

Notes: The table shows the average effect of the EITC and a child care subsidy on consumption, part-time work, full-time work, child care, and child human capital. The sample corresponds to children who are six years of age or less by $t = 2$. To estimate impacts, I take averages of annual effects across all periods for consumption, part-time work, and full-time work, and over $t = 0$ to $t = 2$ for child care.

children under six years of age or less by $t = 2$.

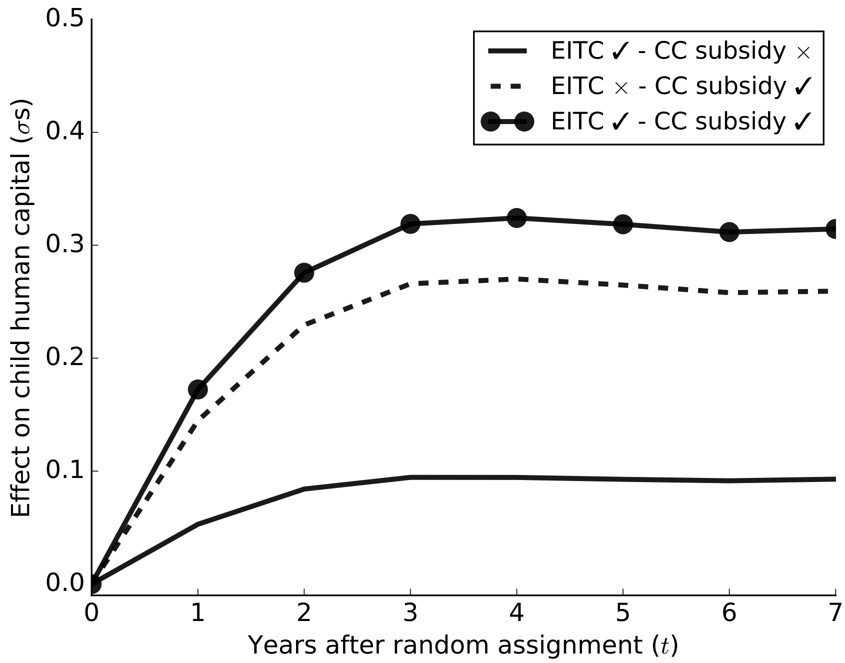
Table 7 presents the average effects of the EITC and the child care subsidy for all periods considered (from $t = 0$ to $t = 7$) on household variables. The EITC increases annual per-capita consumption by $1,100$ dollars, the probability of being employed by two percentage points, and the probability of child care by five percentage points. The child care subsidy has similar effects on employment but raises child care probability by 12 percentage points. Both policies combined have larger effects on the household (column 3).[64]

Figure 7 depicts the impact on child human capital across periods. The effect of any policy combo is increasing in time. Hence, these policies have larger impacts once children are being exposed to them for several years. On average, the EITC increases child human capital by 0.08 standard deviations. The effect of the child care subsidy equals 0.21 on average. Both policies combined increase child human capital by 0.25 standard deviations.[65] Appendix H computes the mediation analysis for these experiments. Consistent with previous findings, more than 90% of the effect of any policy is accounted by the increase in child care use. That is, most of the effects of the EITC on child human capital are explained because individuals use part of the additional money for child care services.

[64] Meyer and Rosenbaum (2001) find that the 1993 EITC expansion increased annual employment of single mothers by 3 percentage points.

[65] Again, note that the effect of two policies combined does not equal to the sum of the effects of policies in isolation. See Section 8.1.

Figure 7: The impact of the EITC and child care subsidy on child human capital (θ_t)



Notes: The figure presents the impact of the EITC and child care subsidy on child human capital. It shows the impacts of the policies in isolation and of both combined on θ_t, for $t = 1, ..., 8$, relative to the baseline scenario of no policies.

Results from this simulation emulate the relatively large effects of EITC cash on child outcomes. The apparent contradiction between the production function estimates indicating a low productivity of money in producing child human capital and the results from the EITC literature can be reconciled because of two reasons. First, given that human capital is a highly persistent process, EITC shocks accumulate in time, generating an increasing treatment effect. After years of exposure to the policy, effects could match those of the literature. The reduced-form evidence on the effects of the EITC on children usually finds a positive, large effect (Maxfield, 2013; Hoynes et al., 2015; Bastian and Michelmore, 2017). A general consensus is that a \$1,000-boost in income from the EITC increases child test scores by about 0.06 standard deviations (similar to the reported impact of Figure 7).. However, the literature has been silent about the timing of this \$1,000-boost. If we take this value as a short-term gain, we end up with a substantial effect of the policy (Nichols and Rothstein, 2016): in five years, the impact would be 0.3 standard deviations.

The second point that rationalizes my results within the literature stems from acknowledging that money has two effects on the child. The first effect is a direct impact on child human capital through the coefficient associated with money (γ_3 from equation 2). The other effect comes from purchasing center-based child care services. In the context of my model, the impact of the EITC on child human capital cannot be regarded as a “pure” money effect (γ_3), since the reduced-form effect of the EITC also incorporates what the individual does with the money—for example, increasing the likelihood of child care use. In fact, as shown, the impact of the EITC on children works mainly through the child care channel.

9 Conclusions

In this paper, I present new evidence on the impact of work-based welfare 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 New Hope 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 income 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. The same result holds if we consider a policy such as the EITC. 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. For any policy, I show that requiring full-time work as a requirement to receive either benefit have a negative effect on child human capital.

Two limitations narrow the external validity 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.[66] Notwithstanding the limitations due to the characteristics of the New Hope experiment, the findings from 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, reduce 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.

[66]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).

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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 of earnings. These parameters do not depend on family composition or other sources of income.

Unlike the earnings supplement, the child allowance component considers *family* annual labor earnings. 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 ($\bar{e}$).[67] 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.[68] For two-parents families,

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

[68] 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.

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):

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

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.[69] 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.[70]

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

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

[70] 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.

$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 than 185% the federal poverty line.[71] 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.

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

B Baseline characteristics by sample

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	28.62	28.45	0.17
	[6.97]	[6.59]	(0.65)
Female (%)	90.65	93.33	-2.68
	[29.18]	[25.00]	(2.59)
African-American, non-Hispanic (%)	62.15	54.67	7.48
	[48.62]	[49.89]	(4.70)
Hispanic (%)	25.23	26.67	-1.43
	[43.54]	[44.32]	(4.20)
White, non-Hispanic (%)	10.75	16.89	-6.14*
	[31.04]	[37.55]	(3.30)
Others (%)	1.87	1.78	0.09
	[13.58]	[13.24]	(1.28)
Never married (%)	63.55	63.11	0.44
	[48.24]	[48.36]	(4.61)
Married living w/ spouse (%)	10.75	10.67	0.08
	[31.04]	[30.94]	(2.96)
Married living apart (%)	8.88	9.33	-0.45
	[28.51]	[29.15]	(2.75)
Separated, divorced or widowed (%)	4.21	4.44	-0.24
	[20.12]	[20.65]	(1.95)
Highschool diploma or GED (%)	50.93	48.00	2.93
	[50.11]	[50.07]	(4.78)
Highest grade completed	11.46	11.19	0.27
	[2.17]	[1.84]	(0.19)
$0 (%)	35.05	40.00	-4.95
	[47.82]	[49.10]	(4.63)
$1-999 (%)	16.36	15.56	0.80
	[37.07]	[36.32]	(3.50)
$1,000-4,999 (%)	24.77	22.22	2.54
	[43.27]	[41.67]	(4.05)
$5,000-9,999 (%)	13.55	12.44	1.11
	[34.31]	[33.08]	(3.22)
$10,000-14,999 (%)	6.54	6.67	-0.12
	[24.78]	[25.00]	(2.38)
$15,000 or more (%)	2.34	2.22	0.11
	[15.14]	[14.77]	(1.43)

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	26.38	26.35	0.03
	[6.31]	[6.51]	(0.78)
Female (%)	92.48	94.16	-1.68
	[26.47]	[23.53]	(3.05)
African-American, non-Hispanic (%)	60.90	49.64	11.27*
	[48.98]	[50.18]	(6.04)
Hispanic (%)	27.07	32.85	-5.78
	[44.60]	[47.14]	(5.59)
White, non-Hispanic (%)	11.28	15.33	-4.05
	[31.75]	[36.16]	(4.15)
Others (%)	0.75	2.19	-1.44
	[8.67]	[14.69]	(1.47)
Never married (%)	69.17	71.53	-2.36
	[46.35]	[45.29]	(5.58)
Married living w/ spouse (%)	6.02	9.49	-3.47
	[23.87]	[29.41]	(3.27)
Married living apart (%)	6.77	8.03	-1.26
	[25.21]	[27.27]	(3.20)
Separated, divorced or widowed (%)	5.26	2.19	3.07
	[22.41]	[14.69]	(2.30)
Highschool diploma or GED (%)	50.38	51.09	-0.72
	[50.19]	[50.17]	(6.11)
Highest grade completed	11.43	11.27	0.16
	[2.02]	[1.80]	(0.23)
$0 (%)	31.58	40.88	-9.30
	[46.66]	[49.34]	(5.85)
$1-999 (%)	21.05	16.06	4.99
	[40.92]	[36.85]	(4.74)
$1,000-4,999 (%)	24.06	24.09	-0.03
	[42.91]	[42.92]	(5.22)
$5,000-9,999 (%)	14.29	13.14	1.15
	[35.13]	[33.91]	(4.20)
$10,000-14,999 (%)	4.51	3.65	0.86
	[20.83]	[18.82]	(2.41)
$15,000 or more (%)	3.01	2.19	0.82
	[17.14]	[14.69]	(1.94)

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 Treatment effects of New Hope

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 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. 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.[72] 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,

[72] 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.

the year-two survey only asks about "last month's income," so income from administrative sources and surveys cannot be directly compared.

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

Measure. 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 4). I consider three mean-tested programs: the EITC, AFDC, and Food Stamps payments.

D.1 The EITC

The EITC parameters vary by state, year, and the number of children (k_t).[73] 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 by 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 5 years. In terms of the model then, a W-2 salary becomes part of the potential wage offer (equation 3).

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.[74] 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.

[73] The federal parameters can be found at http://www.taxpolicycenter.org/sites/default/files/legacy/taxfacts/content/PDF The parameters for the state of Wisconsin are obtained from http://users.nber.org/~taxsim/state-eitc.html.

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

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 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:[75]

$$E < 1.3e,$$

$$E_n < e,$$

where net income follows[76]

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

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.[77]

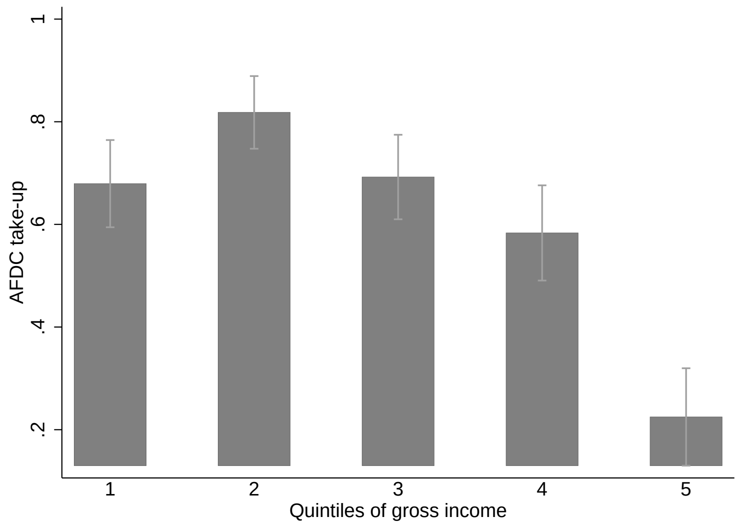
[75] Also, if a family is living only with AFDC payments, then it is automatically eligible. For the purpose of this paper, I assume that if a participant is not working, then she is eligible for SNAP payments.

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

[77] Maximum allotments ($MaxB$) are taken from http://www.fns.usda.gov/snap/fy-2004-allotments-and-deduction-information. See https://www.ssa.gov/oact/cola/colaseries.html for cost-of-living adjustments. For poverty guidelines, see https://www.ssa.gov/policy/docs/statcomps/supplement/2014/3e.html#table3.e8.

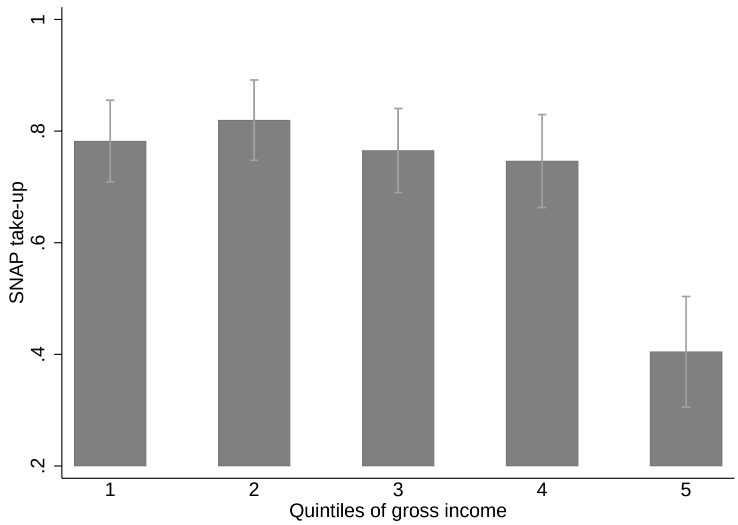
D.4 Take-up rates of AFDC and SNAP

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).

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 Identification of the production function

In this appendix, I show how we can identify the human capital production function (equation 2) using ordinal measures of academic achievement. The proof borrows insights from Cunha et al. (2010) and Agostinelli and Wiswall (2016) in showing the identification of a production function under a particular measurement error structure.

I focus on the following production function:

$$\ln \theta_{t+1} = f(\theta_t, c_t, \tau_t) + \mu cc_t \mathbb{I}\{a_t \leq 6\} \tag{E.1}$$

where $f(.)$ is such that, for some point $(\theta_t^{'}, c_t^{'}, l_t^{'})$, $f(\theta_t^{'}, c_t^{'}, l_t^{'})$ does not depend on an unknown coefficient.[78] The above function describes a technology that varies by child care choice (and thus by age), but it is otherwise constant in time—a key feature of the identification result.

The measures of academic achievement are ordinal variables. These measures rank the child in the classroom academic achievement distribution. For a measure M_t in period t, we have

$$M_t = \begin{cases} 1 & \text{if } \ln \theta_t + \epsilon_t^z \leq \kappa_{1,t} \\ 2 & \text{if } \kappa_1 < \ln \theta_t + \epsilon_{t,m}^z \leq \kappa_{2,t} \\ \vdots & \\ 5 & \text{if } \ln \theta_t + \epsilon_t^z > \kappa_{4,t}. \end{cases} \tag{E.2}$$

where

$$\epsilon_t^z \sim N(0,1) \qquad \forall t. \tag{E.3}$$

Underlying equation (E.3) there are two essential assumptions. First, the coefficient associated to $\ln \theta_t$ equals 1 for all t—a classical measurement-error model. Second, the cutoffs are constant across child age and child care types.

The problem is to identify (E.1) and the parameters of the measurement system (E.2), given (E.3). I follow Agostinelli and Wiswall (2016) to prove the following Lemma.

Lemma 1. *Suppose the production function and the measurement system follow (E.1), (E.2), and (E.3). Then* $\Phi^{-1}\left[Pr\left(M_{t+1} = 5 \mid \ln \theta_t = \bar{\theta}, \ln c_t = \bar{c}, \ln l_t = \bar{l}\right)\right]$ *(where* $\Phi(.)$ *denotes a standard normal cdf) is identified with two measures* M_t *and* M_{t+1} *and it is equal to* $f\left(e^{\bar{\theta}}, e^{\bar{c}}, e^{\bar{l}}\right) - \kappa_{4,t+1}$.

Proof. To simplify notation, let us abstract for a moment of any age-induced difference in the technology of human capital, and so $\ln \theta_{t+1} = f(\theta_t, c_t, l_t)$. First, note that the cutoffs from period t $(\kappa_{j,t})$ are identified by the normality assumption on the measurement error.[79] Second, given equations (E.1) and (E.2),

[78] Agostinelli and Wiswall (2016) introduces the concept of "known location and scale" (KLS). A production function is KLS if, for two non-zero vectors $(\theta_t^{'}, c_t^{'}, l_t^{'})$ and $(\theta_t^{''}, c_t^{''}, l_t^{''})$ such that $\theta_t^{'} \neq \theta_t^{''}$, $c_t^{'} \neq c_t^{''}$, and $l_t^{'} \neq l_t^{''}$, $f(\theta_t^{'}, c_t^{'}, l_t^{'})$ and $f(\theta_t^{''}, c_t^{''}, l_t^{''})$ do not depend on unknown parameters. For the production function from equation (2), the KLS property holds only if the sum of the coefficients sum up to 1, that is, a constant-return-to-scale production function. Because I am assuming a classical measurement error structure, I do not need the production function to be KLS.

[79] The proof follows the standard discrete-choice analysis. In general, a constant term and the variance are not identified in an discrete-ordered framework.

$$\Phi^{-1}\left[Pr(M_{t+1}=5 \mid \theta_t=\bar{\theta}, c_t=\bar{c}, l_t=\bar{l})\right] = f\left(e^{\bar{\theta}}, e^{\bar{c}}, e^{\bar{l}}\right) - \kappa_{4,t+1}.$$

Similarly for period t, we can express $\ln \theta_t = \bar{\theta}$ as $\bar{\theta} = \Phi^{-1}\left[Pr\left(M_t = 5 \mid \theta_t = \bar{\theta}\right)\right] + \kappa_{4,t}$, where $\kappa_{4,t}$ is known and $\Phi^{-1}\left[Pr\left(M_t = 5 \mid \theta_t = \bar{\theta}\right)\right]$ can be constructed using observed data.

Hence,

$$\begin{aligned}\Phi^{-1}\left[Pr(M_{t+1}=5 \mid \theta_t=\bar{\theta}, c_t=\bar{c}, l_t=\bar{l})\right] = \Phi^{-1}\{Pr(M_{t+1}=5 \mid \bar{\theta} = \Phi^{-1}\left[Pr\left(M_t=5 \mid \theta_t=\bar{\theta}\right)\right] \\ + \kappa_{4,t}, c_t=\bar{c}, l_t=\bar{l})\}\end{aligned}$$

Because the expression $\Phi^{-1}\left[Pr\left(M_t = 5 \mid \theta_t = \bar{\theta}\right)\right] + \kappa_{4,5}$ is known for any $\bar{\theta}$, the equation above shows that we can identify $\Phi^{-1}\left[Pr(M_{t+1}=5 \mid \theta_t=\bar{\theta}, c_t=\bar{c}, l_t=\bar{l})\right]$ with data on M_t, c_t, and l_t. □

Now we can use $\Phi^{-1}\left[Pr(M_{t+1}=5 \mid \theta_t=\bar{\theta}, c_t=\bar{c}, l_t=\bar{l})\right]$ to identify the production function. This result is summarized in the following proposition.

Proposition 1. *Suppose that (i) the conditions from Lemma 1 hold and (ii) for some point* $(\theta_t^{'}, c_t^{'}, l_t^{'})$*, f(.) is known (do not depend on unknown coefficients). Then the technology of academic skills formation (equation E.1) is identified.*

Proof. Let us start with the production function of a young child ($a_t \leq 6$) in home care ($cc_t = 0$). Using Lemma (1), we can identify $\Phi^{-1}\left[Pr(M_{t+1}=5 \mid \theta_t=\bar{\theta}, c_t=\bar{c}, l_t=\bar{l})\right]$ for any $\bar{\theta}, \bar{c}$, and $\bar{l} \in \mathbb{R}$. Furthermore, we can exploit the the fact that we know the value of $f(.)$ for some point to eliminate the unknown parameter $\kappa_{5,t+1}$. Choose a point $(\hat{\theta}, \hat{c}, \hat{l})$ such that $f\left(e^{\hat{\theta}}, e^{\hat{c}}, e^{\hat{l}}\right) = \alpha$ is known, and note that

$$\begin{aligned}\Phi^{-1}\left[Pr(M_{t+1}=5 \mid \theta_t=\bar{\theta}, c_t=\bar{c}, l_t=\bar{l})\right] - \Phi^{-1}\left[Pr(M_{t+1}=5 \mid \theta_t=\hat{\theta}, c_t=\hat{c}, l_t=\hat{l})\right] = \\ f_y\left(e^{\bar{\theta}}, e^{\bar{c}}, e^{\bar{l}}\right) - \alpha.\end{aligned}$$

Therefore, given that the left-hand side is identified because of Lemma 1, we can identify the production function $f(.)$ in home care by varying $\bar{\theta}, \bar{c}$, and $\bar{l}$ over their support. Since, by assumption, the production of old and young children in home care is the same, we have also identified the production function of old children.

To identify the production function of a child in child care, we need to identify the TFP parameter (μ). To this end, we can exploit the fact that the cutoffs do not vary by child care choices.[80] Given that $f(.)$ is identified for any $\bar{\theta}, \bar{c}$, and $\bar{l}$ and by Lemma 1, we can obtain the TFP term as follows:

$$\Phi^{-1}\left[Pr(M_{t+1}=5 \mid \theta_t=\bar{\theta}, c_t=\bar{c}, l_t=\bar{l})\right] - f\left(e^{\bar{\theta}}, e^{\bar{c}}, e^{\bar{l}}\right) - \kappa_{4,t+1} = \mu,$$

[80]The KLS property precludes from estimating production functions with TFP dynamics (for example, $f(.)+\mu$). By using that the cutoffs are constant within the group of young children, we can recover the TFP parameter in the young child production function. Agostinelli and Wiswall (2016) states a similar argument to identify a general class of production functions.

and so μ is identified.

Finally, $\kappa_{1,t+1}$, $\kappa_{2,t+1}$ and $\kappa_{3,t+1}$ can be identified using any production function. For example, using a similar reasoning to that of Lemma 1, we can identify $\Phi^{-1}[1 - Pr(M_{t+1} \geq 4 \mid \theta_t = \bar{\theta}, c_t = \bar{c}, l_t = \bar{l})]$. Given that $f\left(e^{\bar{\theta}}, e^{\bar{c}}, e^{\bar{l}}\right)$ is identified, then

$$\Phi^{-1}[1 - Pr(M_{t+1} \geq 4 \mid \theta_t = \bar{\theta}, c_t = \bar{c}, l_t = \bar{l})] - f\left(e^{\bar{\theta}}, e^{\bar{c}}, e^{\bar{l}}\right) = -\kappa_{3,t+1}.$$

Following an analogous argument, we can identify $\kappa_{1,t+1}$, $\kappa_{2,t+1}$ and $\kappa_{3,t+1}$. $\square$

F Control function estimation for wage offer

This section describes the procedure to obtain consistent estimates of the wage offer equation using a control function approach. The comparison of these estimates with that of the structural framework provides a simple way of evaluating the validity of structural assumptions.

Consider the log wage equation. Here, we only observe data for those who choose to work. Let $d_i = 1$ denote that individual i works and 0 otherwise. We have that

$$\log w_i = X_i^{'}\beta + \varepsilon_i, \tag{F.1}$$

where $E[\varepsilon_i \mid X_i, d_i = 1] \neq 0$. Suppose that the decision to work depends on X_i and on a vector of variables Z_i not included in equation (F.1). We can define $E[\varepsilon_i \mid X_i, d_i = 1] \equiv \xi(X_i, Z_i)$. If we are able to account for $\xi(X_i, Z_i)$, then we have a well-behaved equation, as follow:

$$\log w_i = X_i^{'}\beta + \xi(X_i, Z_i) + \underbrace{\varepsilon_i - \xi(X_i, Z_i)}_{\nu_i}, \tag{F.2}$$

where $E[\nu_i \mid X_i, Z_i] = 0$.

A flexible way of estimating $\xi(X_i, Z_i)$ is to form polynomials of the propensity score for the probability of working, $p(X_i, Z_i)$. I use the structural model to obtain individual-level estimated values for $p(X_i, Z_i)$. In doing it, I am implicitly using the exogenous shocks to the budget set (differential exposure to changes in welfare, the EITC, and New Hope) as the instruments Z_i. I estimate equation (F.2) by adding third-degree polynomials of $\hat{p}(X_i, Z_i)$ obtained through the structural simulation. I estimate the constant by taking the sample mean of $\log w_i - X_i'\hat{\beta}$, where $\hat{\beta}$ are the OLS coefficients of equation (F.2). Table F.1 show the results.

Table F.1: Auxiliary estimates used in the GII estimation

Variables	Structural	Control function
Age	-0.022	-0.022
Age^2	0.000	0.000
High school	0.227	0.283
log(t)	0.384	0.403
Constant	1.449	1.452

Notes: The table compares the estimated coefficients of the wage offer process obtained from the structural framework (first column) and from the control function approach (second column).

G Auxiliary model

G.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 with a variable capturing the proportion 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. To construct this variable, 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). I construct dummy variables associated to each measure indicating whether the child is in the top 70% of the class. I take the first PCA score as a composite measure of child academic achievement.

G.2 Auxiliary model

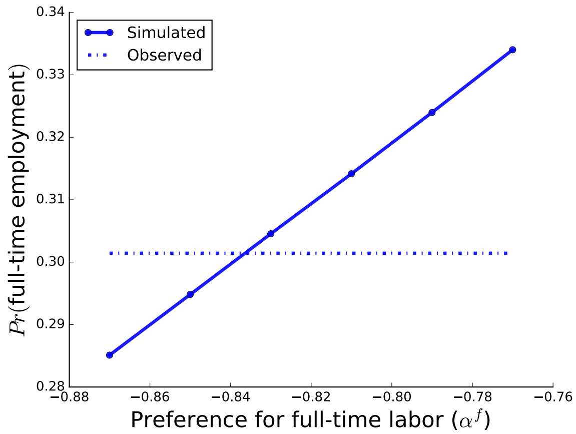
Table G.1: Target moments

Moments	**Simulated**	**Data**	**S.E. data**
A. Labor supply and child care decisions			
$Pr(\text{child care}_t \mid RA = 0)$, $t = 1$ age ≤ 5	0.384	0.384	0.037
$Pr(\text{part-time}_t \mid RA = 0)$, $t = 0$	0.409	0.401	0.020
$Pr(\text{full-time}_t \mid RA = 0)$, $t = 0$	0.309	0.301	0.019
B. $log(wage_t) = X_t'\beta + \epsilon_t$			
Coefficient on high school dummy	0.270	0.275	0.072
Coefficient on time trend	0.066	0.066	0.011
Constant	1.660	1.681	0.074
σ^2	0.453	0.455	0.057
AR(1) shock (ρ)	0.361	0.360	0.058
C. SSRS and household choices			
$Corr[SSRS_2, SSRS_5]$	0.466	0.458	0.076
$Corr[\text{consumption}_1, SSRS_2]$	0.000	0.000	0.000
$Corr[\text{time}_1, SSRS_2]$	0.003	0.003	0.001
$E(SSRS_2 \mid cc = 1) - E(SSRS_2 \mid cc = 0)$	0.152	0.143	0.058
$Corr(SSRS_2, \ln w_0)$	-0.105	-0.103	0.087
D. SSRS ($t = 2$)			
$Pr(SSRS = 2)$	0.180	0.182	0.031
$Pr(SSRS = 3)$	0.355	0.353	0.036
$Pr(SSRS = 4)$	0.212	0.212	0.032
$Pr(SSRS = 5)$	0.133	0.129	0.026
E. $t = 5$			
$Pr(SSRS = 2)$	0.224	0.224	0.028
$Pr(SSRS = 3)$	0.255	0.256	0.029
$Pr(SSRS = 4)$	0.200	0.202	0.027
$Pr(SSRS = 5)$	0.156	0.161	0.025

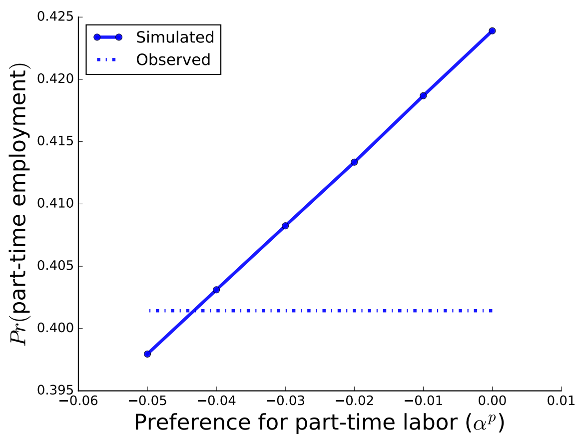
Notes: This table compares the simulated and observed estimated moments that are targeted in estimation. $SSRS_t$ corresponds to overall SSRS measure of academic achievement in period t. In this measure, teachers rank children in a five-point scale based on the overall academic performance in the classroom. $time_t$ corresponds to time with the child (τ_t from equation 7). 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 G.1.

G.3 Local identification from targeted moments

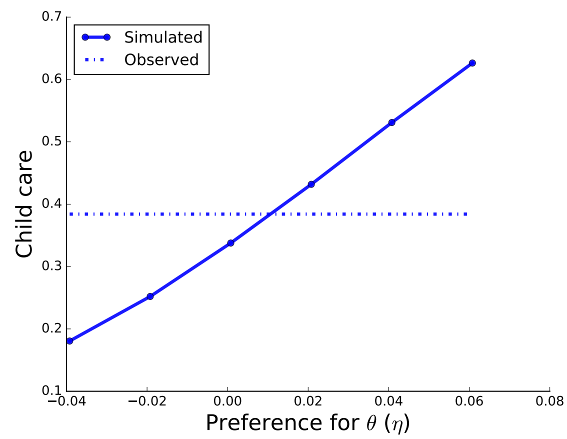
Figure G.1: Target moments locally identify structural parameters: utility function



(a) α^f



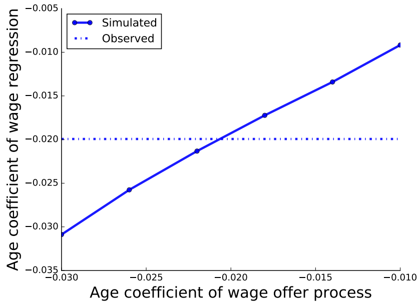
(b) α^p



(c) η

Notes: The figure depicts how a target moment is able to locally identify a structural parameter. The solid line illustrates the simulated moment as a function of a structural parameter. The dashed line shows the observed moment.

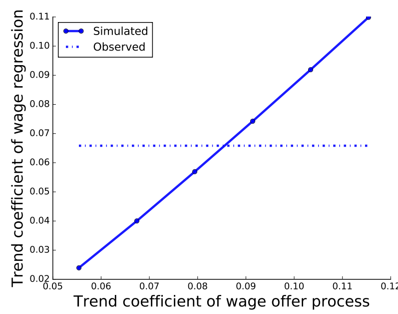
Figure G.2: Target moments locally identify structural parameters: wage offer



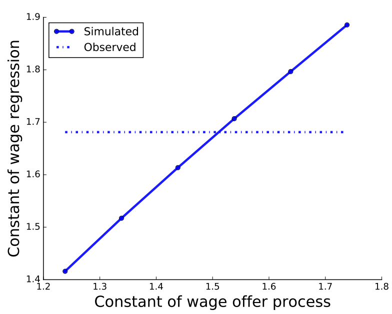
(a) Age

(b) Age^2

(c) High school



(d) $\ln t$



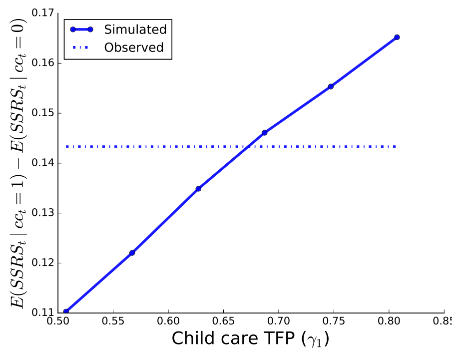
(e) Constant

(f) ρ

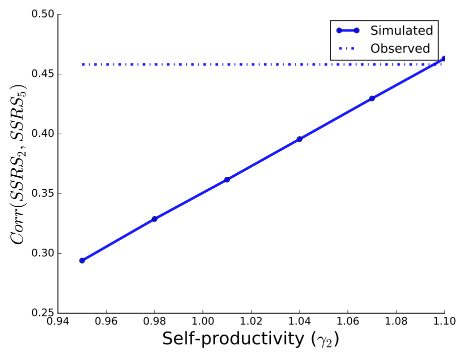
(g) Variance

Notes: The figure depicts how a target moment is able to locally identify a structural parameter. The solid line illustrates the simulated moment as a function of a structural parameter. The dashed line shows the observed moment.

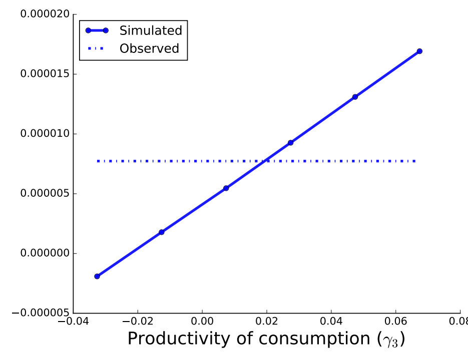
Figure G.3: Target moments locally identify structural parameters: production function



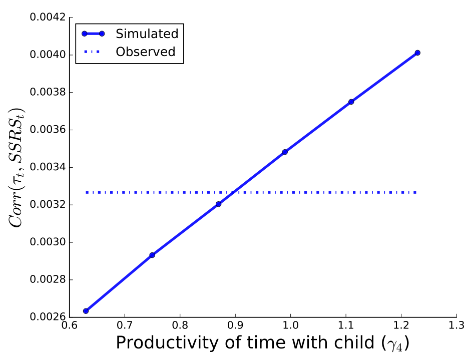
(a) $\gamma1$



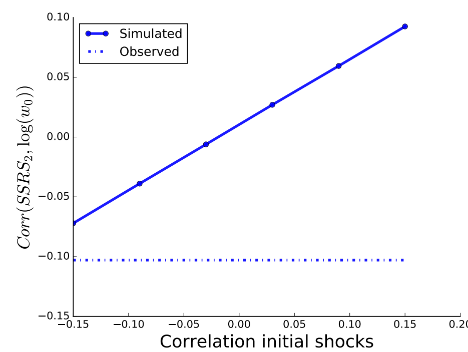
(b) $\gamma2$



(c) γ_3



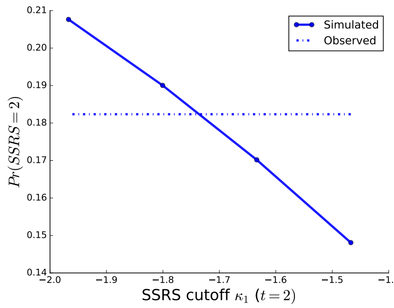
(d) γ_4



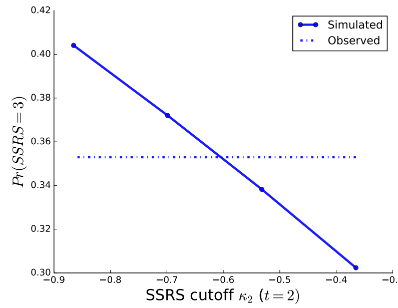
(e) $Corr(\varepsilon_0^{\theta}, \varepsilon_0^{w})$

Notes: The figure depicts how a target moment is able to locally identify a structural parameter. The solid line illustrates the simulated moment as a function of a structural parameter. The dashed line shows the observed moment.

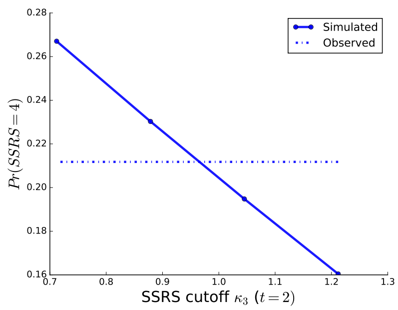
Figure G.4: Target moments locally identify structural parameters: measurement system



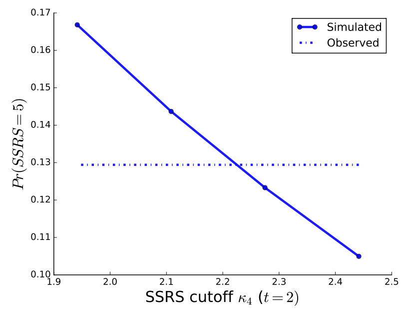
(a) κ_1 $(t = 2)$



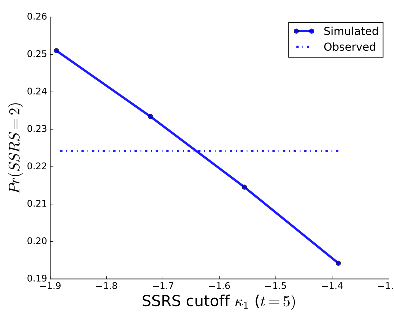
(b) κ_2 $(t = 2)$



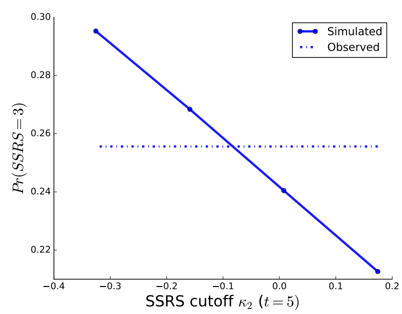
(c) κ_3 $(t = 2)$



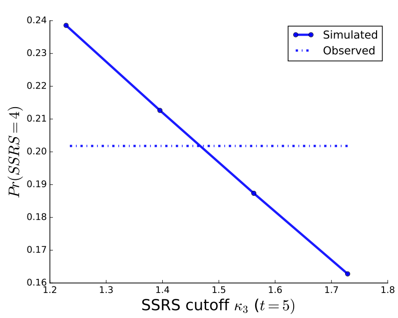
(d) κ_4 $(t = 2)$



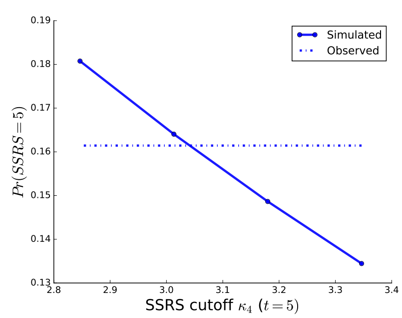
(e) κ_1 $(t = 5)$



(f) κ_2 $(t = 5)$



(g) κ_3 $(t = 5)$

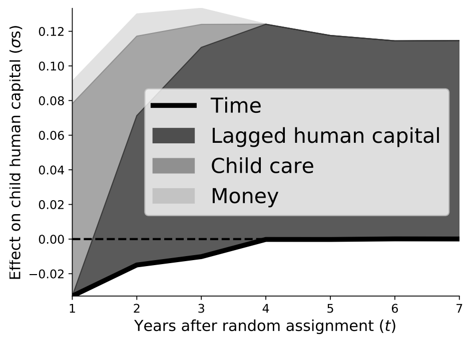


(h) κ_4 $(t = 5)$

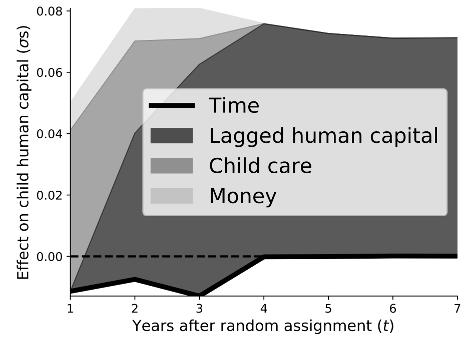
Notes: The figure depicts how a target moment is able to locally identify a structural parameter. The solid line illustrates the simulated moment as a function of a structural parameter. The dashed line shows the observed moment.

H Mediation results

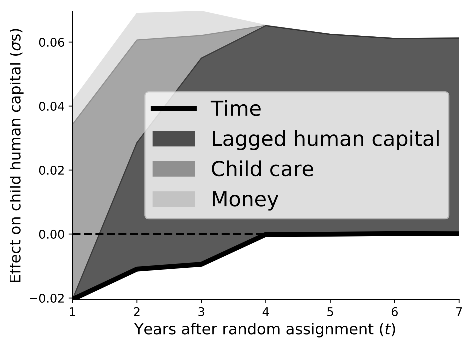
Figure H.1: Decomposition of the impact of New Hope policies on child human capital (θ_t)



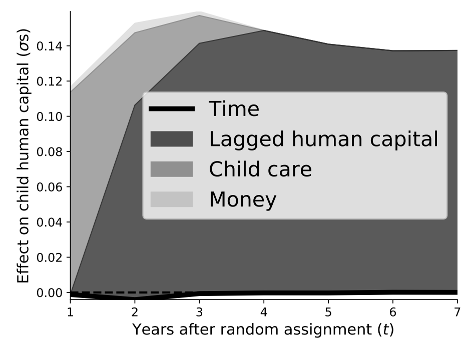
(a) Full treatment



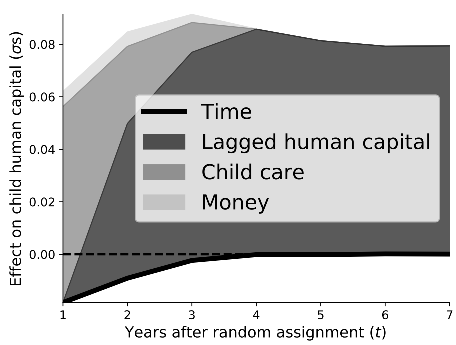
(b) Wage subsidy



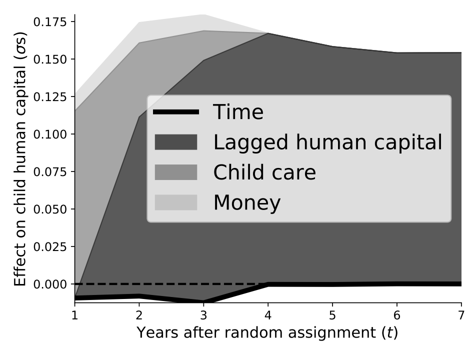
(c) Wage subsidy + Work requirement



(d) Child care subsidy



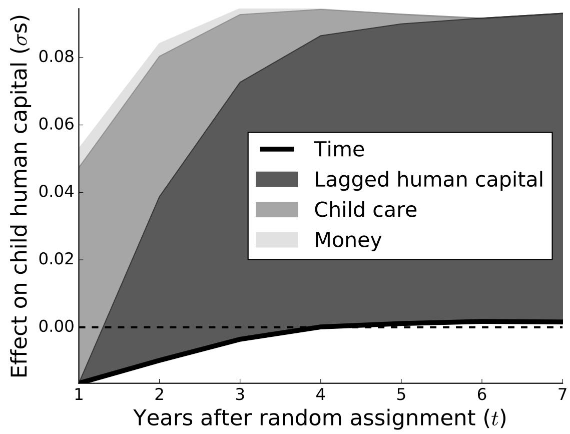
(e) Child care subsidy + Work requirement



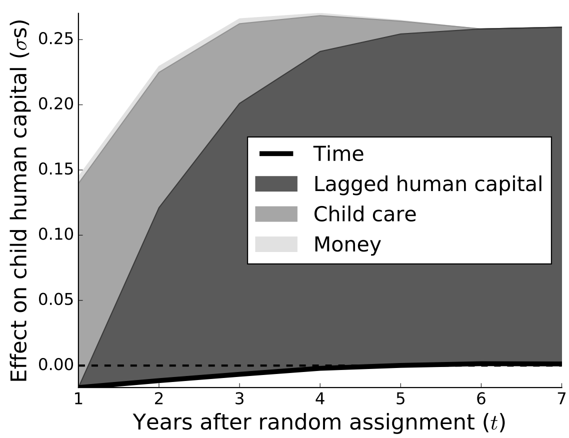
(f) Wage subsidy + Child care subsidy

Notes: The figures plot the share of each input that accounts for the effect of a New Hope policy on child human capital.

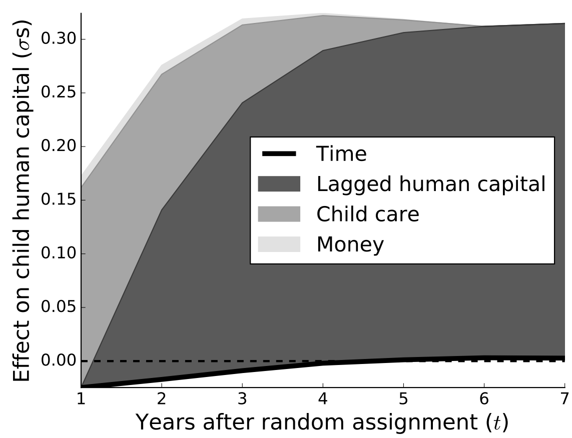
Figure H.2: Decomposition of the impact of the EITC and CCDF on child human capital (θ_t)



(a) The EITC



(b) The child care subsidy



(c) Both policies

Notes: The figures plot the share of each input that accounts for the effect of a policy (the EITC and a child care subsidy similar to Wisconsin's program from CCDF) on child human capital.