Understanding the Effects of Workfare Policies on Child Human Capital*

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Abstract

Workfare policies induce people to work more and thus increase their economic self-sufficiency. However, as parents spend less time at home, workfare policies might have negative effects on children's development. I study the mechanisms by which workfare policies affect children by exploiting experimental evidence from "New Hope" (Milwaukee, 1994-1997). The program randomly assigned an earnings subsidy—similar to the EITC—and a child care subsidy subject to a full-time work requirement to a group of economically disadvantaged families. For families with children who were in their preschool years while they were exposed to New Hope, I find that the program increased labor supply, family income, and center-based child care use during the eligibility period. Notably, the program had sizable short-term effects on child academic performance. Counterfactual experiments from a dynamic-discrete choice model indicate that most of the effect of workfare policies on child human capital is explained because parents, induced by the pro-work incentives embedded in New Hope, enrolled their children in center-based child care.

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1 Introduction

To promote the labor market participation of individuals from low socioeconomic background, policymakers often resort to welfare policies that induce, or directly require, working more hours—also known as "workfare" policies. In the U.S., prominent examples of workfare policies include imposing work requirements and time limits to access welfare, earnings subsidies such as the Earned Income Tax Credit (EITC) and child care subsidies such as the Child Care Development Fund (CCDF).[1] The empirical evidence indicates that some of these workfare policies have succeeded in meeting their original goals—namely, to promote work and increase family income.[2] However, workfare 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]

This paper analyzes how social policies affect human capital development in the early years. Identifying the effects of workfare policies might be a difficult task; as workfare policies are usually implemented alongside others, identifying the effect of a particular policy without holding the other ones constant might bias reduced-form estimates (Chan, 2013; Blundell et al., 2016; Kleven, 2019). To get clean reduced-form evidence of the effects of workfare policies, and study the mechanisms underlying these effects, I use data from the experimental workfare program "New Hope". First, in a reduced-form approach, I show novel evidence on the positive effects of workfare on household choices and child academic achieve-

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[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 recipient's labor supply and income.

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

ment. As the experimental-based variation is not enough to disentangle the household- and policy-level mechanisms explaining the effects of New Hope, I combine the RCT data with quasi-experimental variation coming from workfare policies within a structural model of the household and child human capital. With this framework, I study which type of workfare policy affects child human capital the most and what are the household-level mechanisms that explain these effects. The combination of experimental and structural approaches yield lessons that are relevant to the design and evaluation of workfare policies.

New Hope experimentally tested the effects of two of the most common policy tools to get low-income parents to work: wage and child care subsidies. The program randomly assigned applicants (over 18 years old) to a workfare policy bundle that included an earnings subsidy—similar to the EITC—and a child care subsidy—which resembled the CCDF. Furthermore, to have access to any of these benefits, participants had to prove having worked full time in a given month. Therefore, New Hope represents an ideal laboratory to study the potential effects of workfare on family and child outcomes (Bos et al., 1999; Huston et al., 2001, 2005).

I show novel evidence on the effects of New Hope on families with young children. For women with children in their preschool years while New Hope was in effect, the program increased annual family income by 13%, the probability of being employed in any given quarter by 8 percentage points (from a baseline of 67%), and the likelihood of using child care for young children by 22 percentage points (from a baseline of 40%). Notably, the program had a sizable, positive effect on child outcomes: the program increased academic achievement of children who were in their preschool years while they were exposed to New Hope—measured by teacher's evaluations of student performance when they were in elementary school—by 0.46 standard deviations. Effects for parents and children are much larger in magnitude that those equivalent for parents of older children (Bos et al., 1999; Huston et al., 2003).

I use the experimental setting and exploit quasi-experimental variation to build and estimate a structural model of household choices and child human capital. In the model, a

single-child unitary household chooses hours of work and child care types (informal home care or formal, center-based child care). 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 incorporates different mean-tested and workfare programs, including the AFDC, the EITC, and New Hope. Identification of the model exploits the random assignment of New Hope as well as other policy shocks coming from large shifts in the U.S. social policy: changes in the EITC schedule, the introduction of TANF as a replacement of AFDC, and the implementation of the CCDF.

My counterfactual exercises reveal that center-based child care has a pivotal role when accounting for the effects of New Hope on child human capital. The child care subsidy explains most of the effects of New Hope on child human capital: compared to the earnings subsidy, the child care subsidy produces 2.8 more stock of 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 if New Hope had not included a work requirement. In terms of household choices, two thirds of the effect of New Hope on children is explained because parents, induced by the program, enrolled their children in center-based child care. If New Hope had only included a wage subsidy (without work requirements), the effects would have been mainly explained by the fact that household had more money, net of child care expenditures. Even so, a third of the effect of this hypothetical policy on child human capital can be attributed to a higher use of center-based child care.

This paper contributes to the literature on work-based welfare reforms and child human capital. Most of the reduced-form evidence on the effects of workfare reforms does not quantify the importance of different household-level mechanisms explaining treatment effects and it is unable to identify the effects of programs in isolation and bundled together on parents and child outcomes (Moffitt, 2003, 2016).[4] To take the most common program

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[4]See Moffitt (2003), Moffitt (2016), and Chan and Moffitt (2018) for a review of the extensive evidence on welfare reforms and household outcomes. 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.

analyzed in the literature of workfare reforms and children, there is a growing consensus around the effects of the EITC on child outcomes. Studies show that exposure to the EITC increases short-run test scores, longer run outcomes such as college completion, and even health indicators (Dahl and Lochner, 2012; Maxfield, 2013; Hoynes et al., 2015; Manoli and Turner, 2015; Bastian and Michelmore, 2017). It has been common to attribute the positive reduced-form effects of EITC exposure as causal effects of having more income on child outcomes. However, none of the studies have looked at the role played by other policies implemented at the time[5] or quantified the household behavioral changes explaining the causal effects of EITC exposure on children.[6] In the context of New Hope, my paper studies the mechanisms through which EITC-like subsidies affect child human capital and studies potential complementarities with other workfare policies.[7] In doing so, I establish a significant role for child care as an important underlying mechanism, speaking to an emerging literature showing relatively large effects of child care enrollment and child care policies on children from low-income families (Havnes and Mogstad, 2011, 2015; Kline and Walters, 2016; Cornelissen et al., 2018; Felfe and Lalive, 2018).

I also make a contribution to a literature that studies the effects of welfare reform on families through structural models similar to the one I use in this paper. Bernal (2008), Del Boca et al. (2013), and Mullins (2015) estimate dynamic models of parental choices and child human capital and simulate different policies and their effects on children. My paper, even though resembles in having a structural approach to the problem, is different in various aspects. First, to the best of my knowledge, mine is the first paper to rely both

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[5]In the U.S., important workfare policies—imposition of work requirements under TANF, EITC expansions, and the implementation of the CCDF— have been implemented almost contemporaneously. See Kleven (2019) for an analysis showing how not controlling for other workfare policies can change the estimates EITC exposure on female labor supply.

[6]Nichols and Rothstein (2016) raise a similar point, arguing that EITC effects, coming from commonly used research designs, are difficult to interpret as the effects of pure "income" without identifying the contribution of underlying intermediate mediators.

[7]Agostinelli and Sorrenti (2018) find that negative effects of maternal labor supply are concentrated among low-educated families. They interpret this finding as finding negative effects for families with limited non-parental care alternatives, such as center-based child care. This interpretation is directly confirmed in my paper.

on experimental and quasi-experimental variation to study the effects of welfare policies on child outcomes. Second, in the case of Bernal (2008) and Del Boca et al. (2013), they do not model the welfare system, and thus cannot embed their analysis within a context of an actual policy shock and use it as a source of identification for their models (Eissa and Hoynes, 2004; Meyer and Rosenbaum, 2001; Dahl and Lochner, 2012; Chan, 2013; Blundell et al., 2015; Agostinelli and Sorrenti, 2018). Third, these papers do not consider the center-based child care choice, even though it turns out to be an important driver of the results.[8]

Finally, I provide novel evidence to the early New Hope literature (Huston et al., 2001, 2005, 2011). This group of studies show positive effects of the policy on the academic achievement of participant's children, specially for boys. I show that most of the results are explained by the sizable effects for young children (that is, those who were in their preschool years while under New Hope). Furthermore, by exploiting the structure of my model, I provide new evidence on the effects on children of the individual New Hope policies as well as revealing potential complementarities between them.

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

2   The New Hope welfare model and context

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

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[8]Verriest (2018) does consider time in center-based child care but focuses on the effects of income shocks and subsequent changes in the bargaining power of couples and how it affects child cognitive development.

enhanced existing work incentives.[9]

Applicants living in Milwaukee, Wisconsin, were recruited in two economically disadvantaged neighborhoods.[10,11] 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.[12] 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).[13] Beginning at baseline recruitment and lasting for 36 months, a randomly selected group of applicants had access to various benefits. In this paper, I focus on two elements of the New Hope package: the earnings subsidy 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 earnings subsidy

Figure 1, panel (a), illustrates the earnings subsidy design for a family with one earner and one child.[14] To show how the schedule looks across the distribution of ex-ante labor earnings, the figure assumes no work requirements.[15] The New Hope earnings subsidy complements the EITC subsidy. In the figure, the earnings subsidy is represented as the difference between the dashed and solid lines—that is, the New Hope subsidy is positive as long as the New Hope

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

[10]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).

[11]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).

[12]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).

[13]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).

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

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

Figure 1: New Hope earnings subsidy and child care subsidy

(a) earnings subsidy

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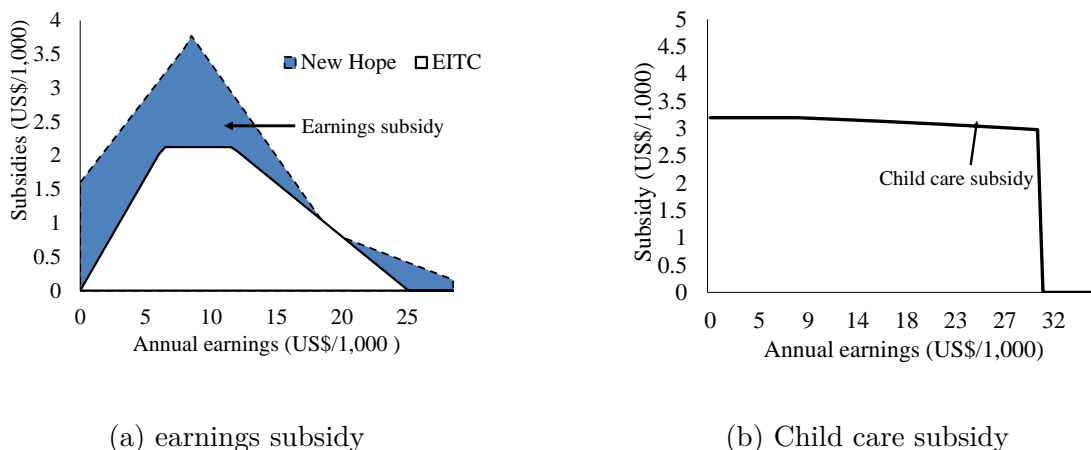
Notes: Panel (a) compares the New Hope and EITC design as a function of annual earnings. The solid line shows the EITC earnings subsidy. The difference between the dashed and the solid line represents the New Hope supplement, for each level of earnings, assuming no work requirement. Panel (b) illustrates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

schedule stays above of that of the EITC.[16] Because the earnings subsidy 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 earnings subsidy decreased with time.

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

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[16]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.

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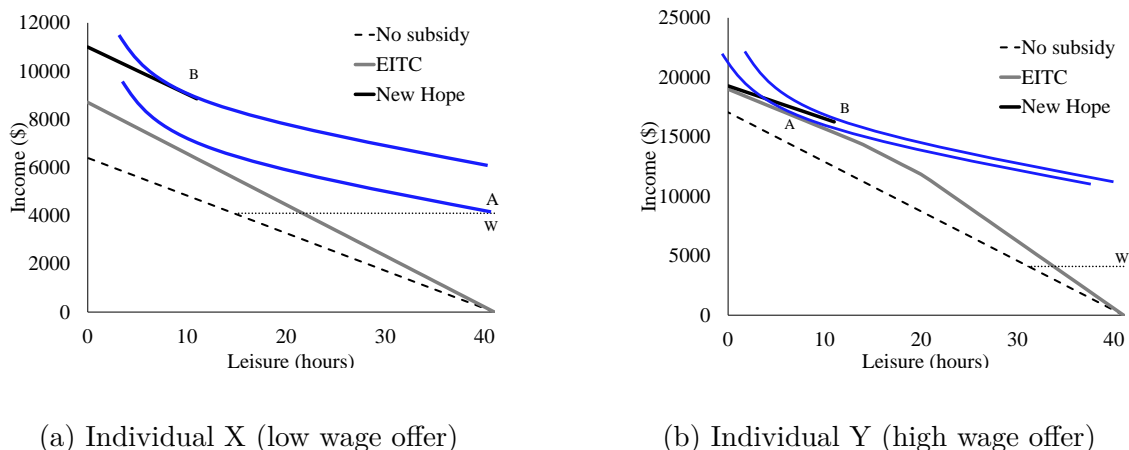
Notes: The figure illustrates extensive- and intensive-margin responses to New Hope. For individuals with two different wage rates and same structure of preferences, it presents individuals choices under different budget sets in the income-leisure plane. Since New Hope requires working 30 hours or more,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

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. In contrast, Y would work more than 30 hours a week. If X and Y were in the treatment group, they would choose to allocate at point B. Compared to point A, X would work more hours and receive more income. Y would earn more as well. However, Y works more or less compared to the counterfactual of not having the program, depending on the relative magnitudes of income and substitution effects. Overall, the New Hope earnings subsidy should have a non-negative effect on income and an ambiguous effect on hours worked.[18]

Because the earnings subsidy affects parental time allocation, it can also produce effects on child outcomes. Suppose that labor supply causes a negative effect on child human capital, while income a positive effect (Bernal, 2008; Dahl and Lochner, 2012). Leaving

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

aside the child care subsidy component for a moment, the effect of the earnings subsidy is ambiguous, and depends on the relative strength of intensive- and extensive-margin labor supply responses and the relative productivity of income and time with the child in the production function of child skills.[19]

2.2 The child care subsidy

Figure 1 (panel b) depicts the child care subsidy schedule for the case of a single-child household paying $3,600 a year for child care, without work requirements. The subsidy amount is stays relatively flat and ends abruptly at a predetermined earnings cutoff. Thanks to the subsidy, families paid a relatively small copayment. Among those who used the child care benefit, the total average cost of child care expenditures was $9,000 a year, or 74% of the average annual income of the control group at baseline. Following the subsidy formula, New Hope would cover 95% of this cost. The child care subsidy was used by both preschoolers and school-age children up to 13 years of age. In the case of school-age children, the child care subsidy covered "extended-day programs," that is, after-school care at the child's school or at another center. Both for preschoolers and school-age children, child care centers must have been licensed by the state of Wisconsin.

Economically disadvantaged families had access to a number of child care programs offered by the Milwaukee's welfare department—with reimbursement rates and subsidy limits that were similar to the New Hope design (Brock et al., 1997).[20] However, families in the New Hope program had some clear advantages over families using the public system. First, participation in New Hope increased their chances of finding low-cost child care services. Parents in the public system under AFDC, for example, usually faced long waiting lists to

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[19]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.

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

apply for public child care subsidies. For families who were not in the welfare system, finding a low-cost child care provider was even harder (for example, obtaining a Head Start slot was almost impossible).[21] In contrast, New Hope beneficiaries enrolled their children in any of the county- or state-licensed child care centers available in the city. Second, qualitative evidence indicates that families who were eligible for public child care programs struggled to comprehend and navigate Wisconsin's complex system (Bos et al., 1999; Blau, 2003). As New Hope gathered all subsidies into one single program, families under New Hope benefited from a simpler system. Moreover, families could reach out to New Hope representatives whenever they had questions regarding their benefits, or if they could not find suitable child care facilities in the city.

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

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

human capital depends on the productivity of child care relative to that of labor supply in the human capital technology. Therefore, as with the earnings subsidy, theory does not give a clear prediction on the sign of the effect of the child care subsidy on child outcomes.

2.3   The work requirement

To receive any of the subsidies of the program in a given month, the participants had to 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 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.

Relative to a workfare policy without a work requirement, introducing such condition can impact household behavior, affecting the effectiveness of the program. Suppose an individual working part-time under a workfare policy with no work requirements. Since working full-time is costly (reduced leisure time) she might not be willing to accept this condition, which leave her without accessing the income and child care subsidy. Alternatively, the benefits coming from these subsidies can more than compensate the associated cost of working full time. Therefore, the effects of introducing a work requirement to a workfare policy on labor supply, income, and child care use are ambiguous. Given this ambiguity in the effects of the work requirement on household choices, we cannot predict exactly what would happen with the production of child human capital as well.

3   Data

To evaluate the intervention's impact, data on participant's labor market outcomes and families up to eight years after baseline was collected. This section describes available data

and sample selection.

3.1 Data sources

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

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

Child care. I construct the child care variable using the New Hope surveys. In the second-year survey, individuals were asked about all regular child care arrangement for the past two years. Possible child care arrangements in the survey are: (i) Head Start; (ii) preschool, nursery school, or a child care center other than Head Start; (iii) school-based extended day program; (iv) another child care other than in someone's home; (v) a person other than

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a member of the household; (vi) another member of the family of household; and (vii) no arrangements. Participants reported the number of months spent in each case (except for number (vii)). I consider a formal child care arrangement categories (i)-(iv), and an informal child care the rest of them. I define $cc_t = 1$ if the child (as declared by the parent) spent the maximum number of months in categories (i)-(iv), and 0 otherwise.

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

3.2 Sample selection

In my analysis, I exploit data from two samples. 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. Out of the original $1,357$ baseline sample, 641 adults have at least one child.[24] My reduced-form estimates and structural framework uses data only for

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

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

[24]Up to two children per family were selected to be part of the CFS. According to Miller et al. (2008), if more than two children were potentially eligible to participate in the CFS survey, only two of them were

the 585 women of the CFS sample. For this sample of women, there are 1,170 associated children. However, for structural estimation, I take the youngest child of each family; thus, my estimation sample equals $N = 585$, where N is the number of women/children in the 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 for an early childhood child care center. In contrast, older children (up to ten years of age) may have used the subsidy to purchase after-school care services. Arguably, the production of human capital under child care and after-school care is not the same and this paper focuses on the impact of being in a early childhood child care center. Second, since test scores were only available for school age children (and for a few children in kindergarten), working with six-year-old children allows me to recover test scores for five- and six-year-old using the New Hope survey of the second year after baseline. The sample of children who were six years old or less by two years after baseline consists of 409 children out of the 1,170 children of female applicants with at least one child.

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

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randomly chosen (with preference given to opposite-sex siblings).

young children, I do not find statistically significant differences—at the 5% level—in the baseline characteristics between experimental groups (Table B.3). Baseline characteristics remained balanced even if I restrict the sample to women with information on the SSRS variable, which exhibits considerable attrition (Table B.4).

4 Treatment effects

Bos et al. (1999) and Huston et al. (2001) document experimental evidence on the effects of New Hope on household behavior and child outcomes.[25] In this section, I follow previous literature and estimate treatment effects on three household variables—income, labor supply, and child care. Later on, I define these three variables the main inputs in the production function of skills and thus are mediators the effects of New Hope on children.[26]

I focus on the effects for families with relatively young children. For the purpose of these estimates, I define "young" as a child that was four years of age or less at the baseline year. This choice allows comparing families who faced New Hope while their children were in their preschool years versus families whom children made the transition or they were at least in primary school during the New Hope period. This comparison is novel for the New Hope literature and reveals substantial heterogeneity in treatment effects, as I show next.

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

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

[26]The estimated treatment effect of New Hope on the SSRS variable for young children disappears when I control for income, labor supply, and child care. See Table 1 for the estimation of treatment effects on the SSRS without control variables.

Figure 3: Treatment effects on child care probability
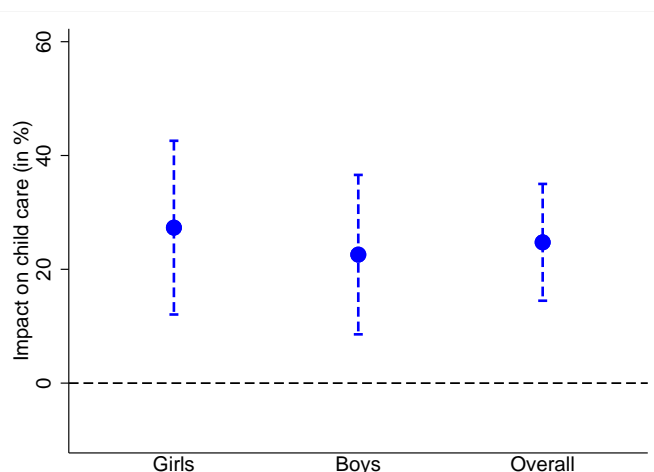
Notes: The figure plots treatment effects on child care use. The dependent variable equals 1 if the child used child care (Head Start, preschool, nursery school, or another child care other than someone's home) and as 0 if the child received home care (stayed at home with another family member or attended any other informal type of care). I show 95

Figure 4 presents treatment effects on income. The income variable includes data on earnings, simulated EITC payments, and welfare payments (see Section 3 for details). I show effects for two different samples: women whose youngest child was four years of age or less at baseline and women whose youngest child was older than four at baseline. Even though estimates are imprecise, the figure shows a clear difference in the treatment effects across these two sub-samples: treatment effects on income for families with young children are larger than those for families with relatively older children. For the first sub-sample and during the New Hope period, New Hope increased annual family income by 1,600 dollars on average (a 13 increase from the baseline), with a statistically significant effect of 2,193 dollars one year after baseline. Furthermore, treatment effects seem to have a constant effect in time, even after New Hope ended. In contrast, as I show below, treatment effects on child outcomes exhibit a clear fade-out pattern, which gives us a first hint that income cannot be the main mediator in explaining effects on child outcomes.

Figure 5 presents treatment effects on employment. The employment variable is defined as a dummy variable that takes the value of 1 if the individual shows a positive earnings record in a quarter and 0 otherwise. The baseline mean over the period I study equals
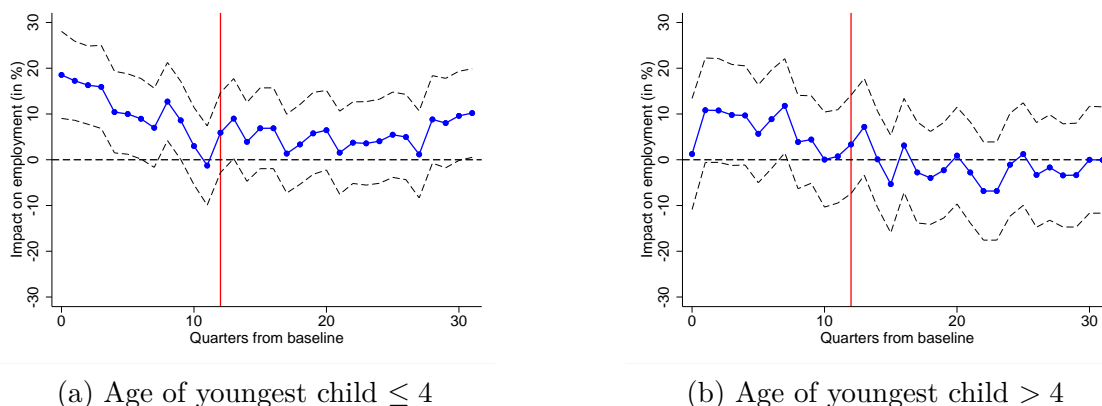
Figure 4: Treatment effects on income
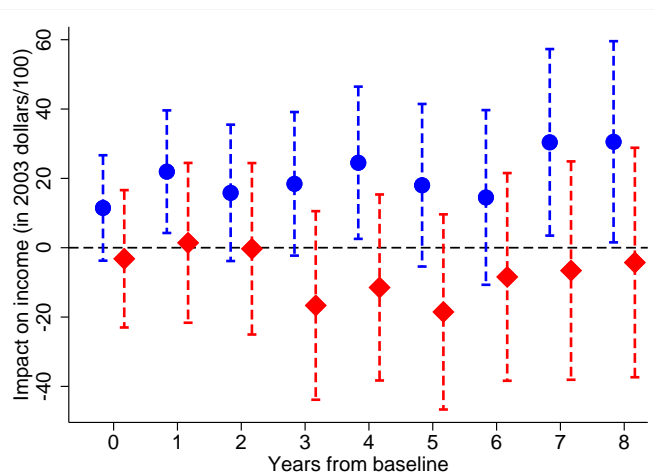
70%. Panel (a) shows effects for women with young children while panel (b) for women with older children. Results show larger labor-supply effects for the sample of women with young children. For this group and while New Hope ran, treatment effects average 8 percentage points from a baseline of 67%. Furthermore, treatment effects on employment are larger at the beginning of the New Hope period (up to 19 percentage points) and becoming statistically insignificant a few quarters before the end of the program, which is consistent with the fact that the New Hope treatment "intensity" decreased as the EITC schedule improved during the years.

Effects on child outcomes Table 1 presents treatment effects on child outcomes. I estimate treatment effects using the SSRS variable expressed in standard deviations. Since sample size is much smaller in these regressions, I compute p-values using randomization-based inference, which are shown to be more robust to extreme outlier observations in small samples (Young, 2018). I estimate the effects of New Hope on the SSRS variable for the overall sample of young children and separately by gender. I emphasize gender differences given that consensus in the literature states that the treatment effects were mainly driven by effects for boys. However, results shows that this distinction is not true across children's

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

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

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

age. Columns 1 and 2 depict treatment effects for the overall sample. Panel A show effects for two years after baseline. Treatment effects equals 0.14 standard deviations (column 1) but they are larger for boys (column 2), as the literature points out. Columns 3-6 separate the sample according to the age of the child, following the definition of young and old of this paper. For the younger sample, New Hope boosted the SSRS variable by 0.46 standard deviations (statistically significant at the 5% level), with little heterogeneity by gender. Gender differences are shown mostly in the older sample. Estimated effects are statistically insignificant five and eight years after baseline.[27]

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

So far, I have shown that New Hope had a economically meaningful impact on household behavior and child academic performance. To understand how New Hope affected child human capital through changing household-level choices, I present a dynamic model household choices and child human capital. The model incorporates the economic constraints defined

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[27]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).

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

| | All | | Age baseline≤ 4 | | Age baseline> 4 | |
	(1)	(2)	(3)	(4)	(5)	(6)
A. Two years after baseline						
Treatment	0.143	0.319	0.462	0.533	0.042	0.269
	[0.180]	[0.021]	[0.030]	[0.054]	[0.725]	[0.088]
Treatment×Girl		-0.308		-0.125		-0.412
		[0.131]		[0.757]		[0.077]
Observations	377	377	92	92	285	285
R^2	0.005	0.037	0.057	0.089	0.000	0.034
B. Five years after baseline						
Treatment	0.033	0.276	-0.171	-0.032	0.196	0.570
	[0.725]	[0.042]	[0.213]	[0.865]	[0.108]	[0.001]
Treatment×Girl		-0.459		-0.265		-0.677
		[0.015]		[0.330]		[0.009]
Observations	476	476	219	219	257	257
R^2	0.000	0.021	0.007	0.031	0.010	0.042
C. Eight years after baseline						
Treatment	0.013	0.145	0.123	0.172	-0.098	0.112
	[0.897]	[0.239]	[0.357]	[0.297]	[0.448]	[0.530]
Treatment×Girl		-0.251		-0.040		-0.394
		[0.190]		[0.883]		[0.131]
Observations	459	459	232	232	227	227
R^2	0.000	0.057	0.004	0.074	0.002	0.053

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

by various workfare programs as part of the individual's budget set. Shaped by this policy environment, labor supply and child care choices have effects of the accumulation of 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 baseline year $t = 0$, a forward-looking agent receives the New Hope "shock" and draws an initial value of child human capital. Each period, the agent observes her household composition, a wage offer, and the current level of child human capital and makes labor supply (not working, part-time,

or full-time work) and child care choices (center-based child care or home care) up until the child turns 18 years of age. These choices are shaped by various shocks to the agent's budget set—New Hope and the welfare system—and by a dynamic production function of child human capital. The forward-looking agent makes her choices 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

$$U(c_t, h_t, \theta_t) = \frac{[c_t \exp(\alpha^p \mathbf{1}\{h_t = 15\} + \alpha^f \mathbf{1}\{h_t = 40\})]^{\gamma_c}}{\gamma_c} + \eta \frac{\theta_t^{\gamma_\theta}}{\gamma_\theta}, \tag{1}$$

where h_t are weekly working hours. h_t takes three possible values: 0, 15 (part-time work), and 40 (full-time work). c_t represents monthly disposable income net of child care expenditures, expressed in per-capita units.[28] α^p and α^f capture the utility cost or benefit of part-time and full-time work. θ_t is child human capital. Parents observe a "true" value of child human capital, that is, the 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 a parent that cares for her child's human capital.[29] For married individuals, I assume the principal caregiver of the child is the one who makes all of the choices. Having a spouse affects choices by adjusting consumption per-capita (more mouths to feed but possibly more income) and the budget set (welfare rules differ by marriage status).

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

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

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 equals 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, for a given (θ_t, c_t, τ_t). γ_2 represents the influence of the current stock of human capital on the accumulation of future human capital, and it is sometimes referred as "self-productivity" (Cunha and Heckman, 2006). γ_3 is the effect of "money"—holding fixed labor supply and child care—and γ_4 is the effect of parental time—holding fixed income and child care.

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

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

The logic behind equation (3) is as follows. If the child spends all week in home care ($cc_t = 0$), then labor supply determines how much time the adult spends with the child. There are three possible scenarios. If the individual does not work, then she spends all the

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available time with the child ($\tau_t = \overline{T}$). If she works part time, then she is 20 hours away from home in a week, so $\tau_t = \overline{T} - 15$. Analogously, $\tau_t = \overline{T} - 40$ if she works full time. If $cc_t = 1$, then the child spends 40 hours a week outside the house being cared in a child care center. Hence, if $cc_t = 1$, then $\tau_t = \overline{T} - 40$ no matter how many hours the adult spends working. For school-age children, child care is not an option ($cc_t = 0$), but there is mandatory school. Hence, if $\overline{T} = 168$ (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.[30]

Equations (1), (2), and (3) determine the benefits and costs the agent faces when choosing labor supply and child care. First, child care allows the individual working more and thus having more income without reducing child human capital. Thus, she has more money to consume and produce further child human capital (if $\gamma_4 > 0$). In addition, if $\gamma_1 > 0$, child care has a direct and positive effect on child human capital. Hence, the benefits of child care are twofold: it directly produces child human capital and it lowers the marginal cost of labor supply. Thus, and following (Del Boca et al., 2013), time with the child affects welfare only through changes in child human capital. However, changes in time with the child are followed by changes in labor supply, which does enter directly the utility function.

Second, parental leisure and time spent with the child have the same effect on utility. Following equations (2) and (3), any time allocated outside the labor market (if the child is at home) has a constant effect on child human capital.[31] Therefore, γ_4 in the production function is a weighted average of the effects of active and passive time with the child. 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.

Third, equations (1)-(3) imply that household choices can affect both directly and in-

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

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

directly individual's welfare. Income enters individual's welfare directly each period and indirectly through θ_t. We can interpret the indirect effect in two ways. First, part of what the agent purchases can also affect child human capital (e.g. books, food, etc). Second, having more money at home can relieve stress in the household, which can potentially enhance the parent-child relationship.

An additional child in the family does not directly impact current-value utility or the process of child human capital formation Having more children influences choices only by changing disposable income; an additional child in the household, all else equal, lowers c_t and changes the eligibility for and payments associated to welfare programs. For a family with more than one child, the adult makes her choices taking into account how they impact the human capital of a representative child.[32]

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

$$\ln w_t = X_t^{w'} \beta^w + \nu_t^w,$$
$$\nu_t^w = \rho \nu_{t-1}^w + \epsilon_t^w$$
$$\epsilon_t^w \sim N(0, \sigma_w^2) \tag{4}$$

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

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

she makes her choices.

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

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

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

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

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

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

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

In the equation above, $EITC_t(.)$ corresponds to EITC payments. If the individual is eligible to receive these payments, she always comply.[33] The same happens with the New Hope

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[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

payments, $NH_t(.)$. B_t and $SNAP_t$ are cash transfers from AFDC (or TANF) and Food Stamps (now known as SNAP). As with New Hope and the EITC, and following (Blundell et al., 2016) for the UK context, the individual always takes up the benefits of welfare programs (AFDC and SNAP) conditional on eligibility.[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:

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

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

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

Each of the payment functions $EITC_t(.)$, $NH_t(.)$, $B_t^*(.)$, and $S_t^*(.)$ are given by precise formulas determining eligibility and payment levels. They are a function of the level of earnings, 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]

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.

[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

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 4). In the model, individuals do not face time limits for W-2.[38]

The cost of child care services depend on whether or not the individual is the treatment group and on the probability of receiving a free child care spot. The individual can use free child care services, but slots in the market are limited. Every period, the individual draws a value $\rho_t^c \in \{0, 1\}$ indicating if the individual is offered a free child care slot. If the individual has an offer she can use child care for free only if earnings are below a certain threshold E^*. If she does not has the option of free child care (she was not offered the slot or her earnings are above the cutoff), the parent can pay for child care services, at a known and fixed price p. 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). Any type of informal child care arrangement that might happen in practice when the parent is not at home and the child is not at a center-based child care has zero cost (or, alternatively, p can be interpreted as the relative cost of formal versus informal child care). Formally, let $\delta(\rho_t^c, w_t, h_t, D)$ be the child care cost function, given by:

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

where

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

The individual cannot save or borrow.[39] The individual receives utility from per-capita

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

[39]There is little evidence suggesting that individuals are able to save for future consumption. In the

income net of child care expenditures. Thus, c_t is given by

$$c_t = \frac{I_t - cc_t \mathbf{1}\{a_t \leq 5\}\delta(\rho_t^c, w_t, h_t, D)}{1 + m_t + k_t}. \tag{9}$$

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

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

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

where m_t equals 1 if the participant is married or living with her partner and 0 otherwise, and k_t indicates the number of children in the household. X_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 grouped in the vector $\boldsymbol{s}_t = (D, m_t, k_t, a_t, \theta_t, \boldsymbol{X}, \nu_t^w, \boldsymbol{\rho}_t, p)$, where $\boldsymbol{X} \equiv \left(X^w, X^m, X^k\right)$ contains the wage offer, marriage, and childbearing processes control variables and $\boldsymbol{\rho}_t \equiv \left(\rho_t^E, \rho_t^B, \rho_t^S, \rho_t^C\right)$ the spousal employment indicator, misinformation shocks to welfare take-up and the free child care slot indicator. For a given $\boldsymbol{s}_t$, each period the agent maximizes the present discounted value of the utility stream by choosing labor supply and child care type. Let $\mathcal{C} = \{0, 1\}$ and $\mathcal{H} = \{0, 15, 40\}$ 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

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control group, from the year-five interview, 58% manifested some concern about not having enough money to buy food. Additionally, a large share does not access to banking services, 42% of individuals do not have a checking account, and 52% do not have a savings account.

$(a_t \leq 5)$ 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 of age.

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

$$V_t(\boldsymbol{s}_t) = \max_{j \in \mathcal{J}(a_t)} \{V_t^j(\boldsymbol{s}_t)\} \quad \text{subject to (1)-(11)},$$

$$V_t^j(\boldsymbol{s}_t) = u(\boldsymbol{s}_t, j) + \beta E[V_{t+1}(\boldsymbol{s}_{t+1}) \mid \boldsymbol{s}_t, j] \qquad t < T(a_0), \tag{12}$$

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

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

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

6 Identification and estimation

6.1 Identification

The policy environment within the model offers various sources of exogenous variation that can be exploited for identification. These policy shocks are the end of the AFDC and replacement by the TANF, expansions to the EITC schedule, and the implementation of the large-scale child care subsidy funded by the CCDF. Moreover, cash transfers and sudden changes in payment levels across time depend on family structure, which is a source of exogeneous variation that is commonly used in the reduced-form literature (Eissa and Hoynes, 2004; Meyer and Rosenbaum, 2001; Dahl and Lochner, 2012). Furthermore, there are several discontinuity points in the rules of the different mean-tested programs. In the model, all of these policy shocks shape labor supply and child care decisions without directly changing preferences, the wage offer equation, or the production function. Therefore, identification hinges on the comparison of choices and outcomes across periods (before and after policies are implemented), family composition, and at different points of the wage offer distribution for a given set of parameters determining preferences, wages, and child outcomes.[40]

A key identification issue is the inability of the econometrician to observe child human capital. Instead, the econometrician observes a noisy measure (M_t) of child human capital. Its relationship with child human capital is given by

$$M_t = \kappa_t + \lambda_t \ln \theta_t + \epsilon_t^z \tag{13}$$

where θ_t is observed by the families but not by the econometrician and ϵ_t^z is measurement error. The problem is thus identifying the distribution of unobservables and the production function of child human capital with data on M_t. I assume $\epsilon_t^z \sim N(0, \sigma_t^Z)$, $\kappa_t = 0$, and $\lambda_t = 1$,

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[40]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.

Figure 6: Local identification of the preference for human capital
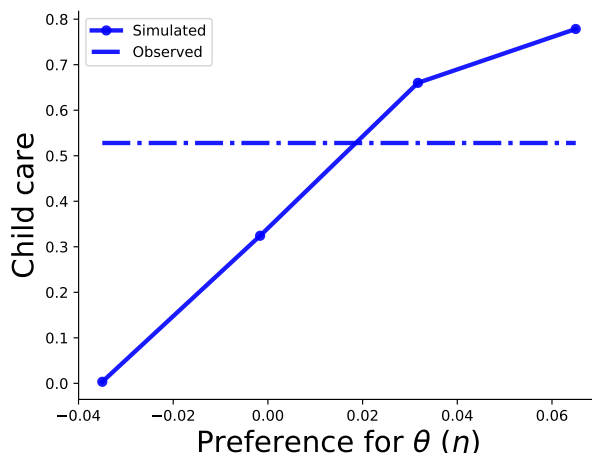
Notes: The figure plots the proportion of children in child care from the model against the structural parameter of preference for human capital (solid line). This parameter is locally identified at the crossing point with the corresponding observed moment (depicted in the dotted line).

which allows for just one measure per period to identify the measurement error variance.

Some non-experimental moments contain identifying information at the local level. To illustrate the sources in the data that contribute to the identification of the structural parameters, Figure 6 plots the relationship between a simulated moment and a structural parameter, holding the rest of the parameters fixed.[41] 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 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" by the chosen moment; 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.

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

6.2 Estimation

To keep estimation computationally feasible, I follow Gourinchas and Parker (2002), De Nardi et al. (2010), Voena (2015), and Blundell et al. (2016) and proceed in two steps. In the first step, I estimate the parameters of some of the exogenous processes straight from the data. In the second step, I estimate the rest of the structural models using the simulated method of moments. I use moments that meet the single-crossing property of the previous section directly in the estimation procedure. I explain the exact procedure next.

External estimation and calibration. Table 2 summarizes the sources for external estimation an calibration. To obtain the parameters governing the probability of being married (m_{t+1}^*) and of childbearing (k_{t+1}^*), consider the following linear probability models:

$$m_{t+1} \;\; = \;\; X_t^m \beta^m + m_t \gamma^m + \epsilon_{t+1}^m, \tag{14}$$

$$k_{t+1} - k_t = X_t^k \beta^k + k_t \gamma^k + m_t \gamma^{k,m} + \epsilon_{t+t}^k. \tag{15}$$

Since I do not have marriage data for two years in a row, I cannot directly estimate the parameters of equations (14) and (15). To circumvent this problem, I estimate a linear probability model of m_{t+1} on m_{t-1} and X_{t-1}^m, and use the resulting reduced-form parameters to identify β^m and γ^m.[42] I implement a similar method to identify β^k, γ^k, and $\gamma^{k,m}$. Given the estimated parameters of equations (14) and (15), the parameters of the binomial distribution determining the probabilities of marriage and childbearing (equations 10 and 11) are given by $m_{t+1}^* = X_t^m \widehat{\beta}^m + m_t \widehat{\gamma}^m$ and $k_{t+1}^* = X_t^k \widehat{\beta}^k + k_t \widehat{\gamma}^k + m_t \widehat{\gamma}^{k,m}$.

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). I set the probability of using a free child care spot equal to 0.57, which

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

is the proportion in the control group of children using Head Start at baseline. I define the probability of receiving AFDC and Food Stamps—conditional on being eligible—as the average take-up observed in the data (60% and 70%, respectively). Finally, I follow Chan (2013) and set the discount factor to $\beta = 0.86$, which is a middle point between the equivalent parameters of Swann (2005) and Keane and Wolpin (2010).

Table 2: Calibrated and externally estimated parameters

Parameter/equation	Source for estimation/calibration	Values
Probability of being married	OLS: m_{t+1} on m_{t-1} and X^m	$m_{t+1}^* = 0.21 - 0.002age + 0.8m_t.$
Probability of childbearing	OLS: $(k_{t+1} - k_t)$ on m_{t-1}, k_{t-1} and X^k	$k_{t+1}^* = -0.11 + 0.05age - +0.0003age^2 - 0.006k_t - 0.1m_t$
Child care price	Bos et al. (1999)	$323 monthly
Free child care probability	Proportion of children on Head Start	0.57
Take-up probabilities of AFDC and SNAP	Average AFDC and SNAP take-up conditional on eligibility	0.6 and 0.7
Discount factor (β)	Chan (2013)	0.86
Curvature parameters	Agostinelli (2018); Low and Pistaferri (2015)	$\gamma_c = -0.56$; $\gamma_\theta = 0.5$

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 s_t contains continuous variables, obtaining an exact solution for $V_t(s_t)$ at every point of the state space is computationally unfeasible. Thus, following Keane and Wolpin (1994) and Keane et al. (2011), I compute $V_t(s_t)$ 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 80 observations. Finally, I use Monte Carlo integration (with 50 draws) to estimate the multivariate integral.[43]

The estimation problem can be stated as follows. Let $\hat{g}$ be the vector of moments extracted from the data. I solve the model $M = 10$ times for a sample size of $n = 692$ children and compute the required moments from simulated data. Let $\{\boldsymbol{\epsilon}_t^m\}_{m=1}^M$ denote the structural random shocks (fixed across the estimation procedure). Let ψ be the vector of structural parameters of the model. Define $\{y_{it}^m(\psi)\}_{m=1}^M$ as the simulated choices associated with the M draws of structural random shocks. Let $\hat{g}^m(\psi)$ be the equivalent moment associated with the m draw. I estimate the structural parameters ψ by solving

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

where $\hat{g}(\psi) = \frac{1}{M} \sum_{m=1}^M \hat{g}^m(\psi)$ and $\hat{g}$ 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). Finally, I use the bootstrap (1,000 samples) to estimate W and compute standard errors using the asymptotic formula given by Gourieroux et al. (1993).

Target moments. Estimation exploits a set of unconditional and conditional moments. The matched moments are non-experimental, while experimental moments are left for validation. Based on the argument given in Section 6.1 (see Figure 6), estimation targets moments that provide identification at the local level.[44] 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

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

[44]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.

time with the child (as defined in equation 3) with the SRS assessment. To estimate the measurement system, I include first and second moments of the sample distribution of SSRS. Finally, to estimate the wage offer and spousal income processes, the auxiliary model includes the OLS coefficients of the corresponding sample regressions in the context of equations (4) and 5.[45] Appendix G shows that the model successfully matches all target moments.

7 Model estimates and validation using experimental data

7.1 Estimated structural parameters

Table 3 presents the estimated structural parameters. For estimation purposes, the baseline sample consists of the CFS sample of children. After removing observations with missing data on household information, estimation uses data on 904 children and of their principal caregivers.

Panel A presents the parameters of the utility function (equation 1). Child human capital is positively valued by the agent: without considering the long-term effects on the human capital stock, the structural estimates imply that the individual is willing to sacrifice almost 500 dollars for a one-standard-deviation increase in the current stock of child human capital, for a given level of instantaneous utility.[46] 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 4). The positive coefficient associated to the trend variable implies that the wage offer increases for

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

[46]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.

Table 3: Estimated structural parameters

Parameter	Estimate	S.E.
A. Utility function		
Preference for part-time work (α^p)	-0.001	0.000
Preference for full-time work (α^f)	-0.175	0.266
Preference for human capital (η)	0.030	0.025
B. Wage offer		
High school dummy	0.213	0.108
Trend	0.096	0.014
Constant	1.480	0.169
Variance of error term	0.282	0.059
AR(1) error term	0.571	0.075
C. Spouse income		
High school dummy	0.073	0.155
Constant	7.191	0.107
SD of error term	0.252	0.070
Employment probability	0.934	0.104
D. Production function		
Child care TFP (γ_1)	0.200	0.151
Lagged human capital (γ_2)	0.881	0.028
Income (γ_3)	0.064	0.124
Time (γ_4)	0.065	0.680
SD $(\sigma_{m,2})$	0.494	0.059
SD $(\sigma_{m,5})$	0.803	0.060
$Corr(\varepsilon_0^\theta, \varepsilon_0^w)$	-0.026	0.083

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

everyone, possibly capturing a growing labor demand.[47] A high school diploma increases the wage offer by 21%, which 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) is bigger and the autocorrelation coefficient of the unobserved component of the wage offer (0.57) is lower compared to what Blundell et al. (2016) find for women 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.

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

I show the estimated parameters of the production function and measurement system in Panels C-E. Consumption has a positive effect on human capital. Assuming no behavioral responses and holding labor supply constant, a 1,000-dollar boost in one period rises child human capital by 7% of a standard deviation the next period, similar ti what is reported in Dahl and Lochner (2012) and.[48] Time at home has a positive effect on children's human capital. Going from $h_t = 40$ to $h_t = 0$ (*ceteris paribus*), assuming no one uses child care, rises child human capital by 3% of a standard deviation, in contrast to studies showing economically meaningful impacts of parental time on child outcomes (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 23% of a standard deviation. Quantitatively similar effects of child care on participant children have been also found in the Head Start literature (Feller et al., 2016; Kline and Walters, 2016). Finally, the human capital production function contains substantial persistence. The relatively high persistence in the production function is a consistent finding in the literature (Cunha and Heckman, 2006; Cunha et al., 2010; Attanasio et al., 2015). A strong persistence component implies that any shock to the human capital process at early ages has almost permanent consequences for skills production in the future.

7.2 Validating model's prediction using experimental-based treatment effects

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,

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

2008; Del Boca et al., 2013).

Figure 7, 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, an almost equivalent effects on child care and (log of) per capita consumption.

Figure 7: Simulated and observed treatment effects

(a) Impact on child care

(b) Impact on log consumption

(c) Impact on hours

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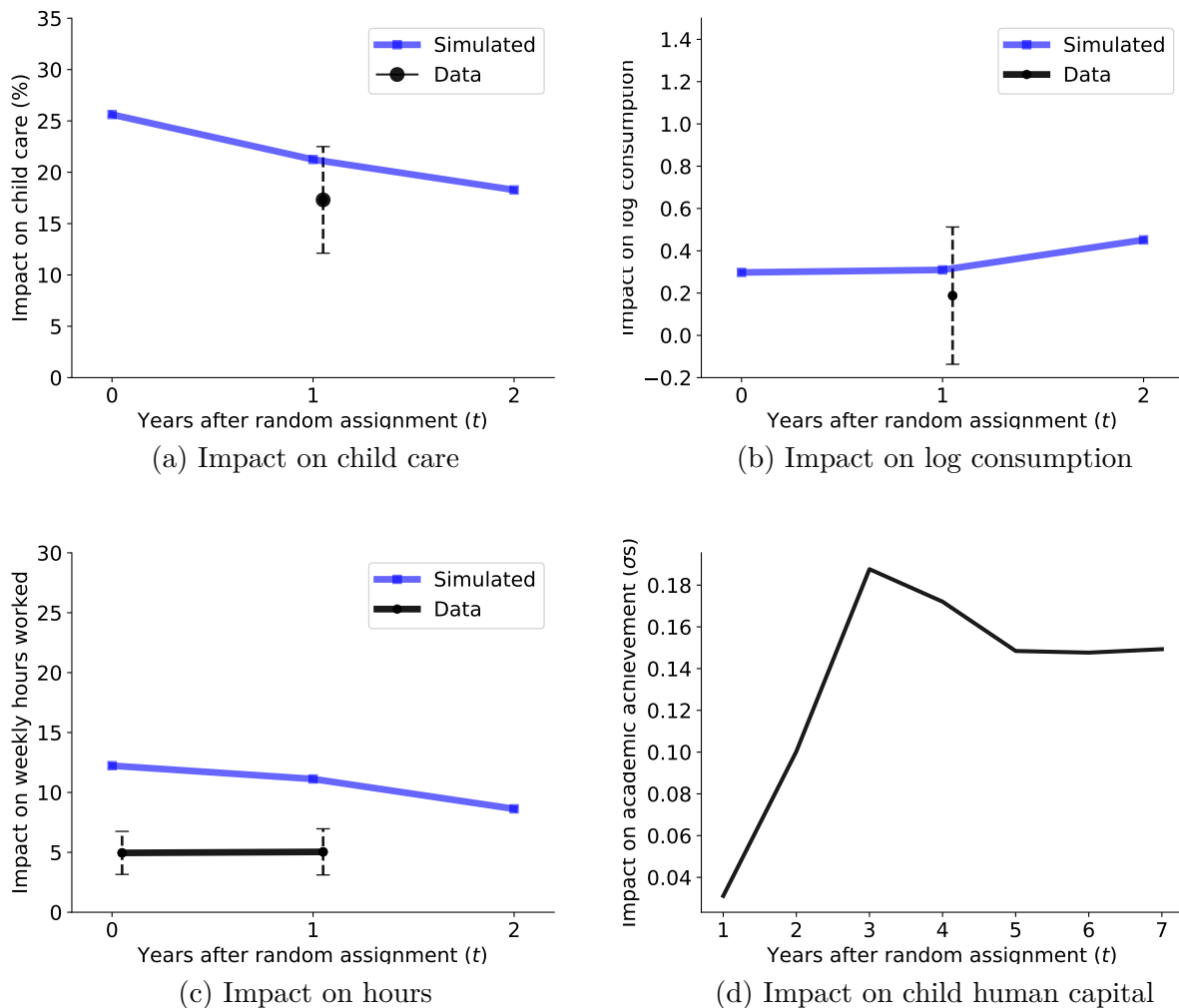
Notes: Panels (a)-(c) compare the simulated and observed treatment effects on household variables. Panel (d) depicts the simulated impact on the observed measure of academic achievement (SSRS).

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, time plays a minor role. This result is explained because the time productivity coefficient is relatively small (see the discussion in the following section). Hence, the upward bias in predicting the effects of New Hope on time 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 7 computes the model-predicted impact on early childhood human capital. The model cannot match the fade-out pattern in the effects on child academic achievement that is observed in the data. Understanding fade-out patterns, while at the same time acknowledging that the production function is highly persistent, is left for future research. Since the structural model cannot replicate these fade-out patterns, I focus my analysis in the effects of New Hope in the very short-term (up to two years after baseline).

8   Understanding the effects of New Hope

8.1   Unpacking New Hope

Grogger and Karoly (2009) suggest that the varied results coming from an array of workfare RCTs may be explained by the different types of policies that each program included. Furthermore, I have shown that New Hope, as a policy package, had economically meaningful effects on families. In this section, I study which components in the New Hope 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. I start by evaluating the effect that income and child care subsidies have on child human capital and then continue to analyze the role played by the full-time work requirement.

I compute the effects of different New Hope policies on children and the family. In these experiments, I change the parameters of the New Hope package and re-compute treatment effects on household behavior and child outcomes under different versions of New Hope. 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 8 (panel a) 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 (0.17 standard deviations two years after baseline) is 2.8 times the corresponding treatment effect of a wage subsidy.

Figure 8: Effects of New Hope policies on child human capital

(a) No work requirements (b) With work requirements
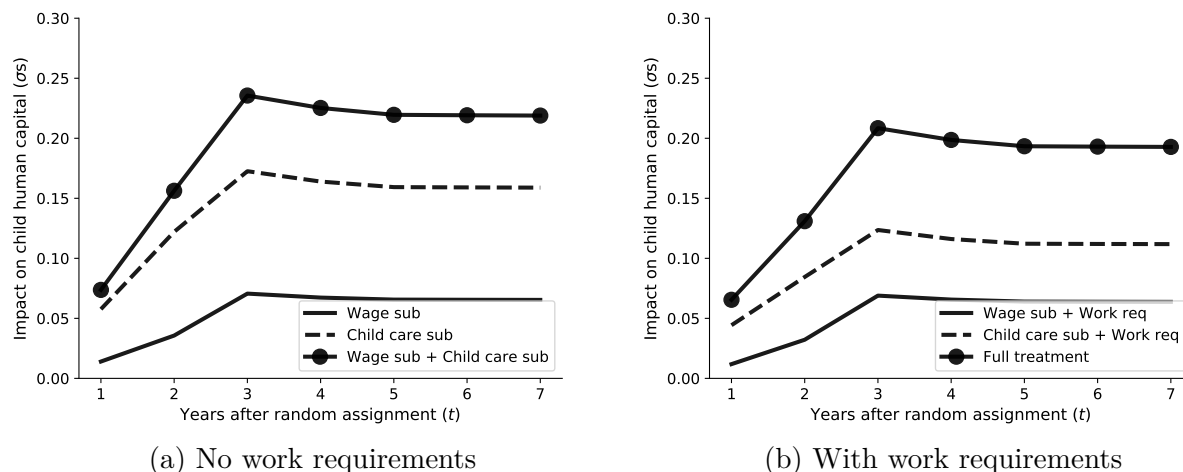
Notes: The figure plots the impact of various combinations of New Hope policies on child human capital. The sample consists of children who were six years of age or less by $t = 2$ years after baseline.

The counterfactual experiments shed lights on the potential complementarities arising from putting wage and child care subsidies together.[49] Note that the actual "effect" on child

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[49]The bulk of the literature evaluating welfare reforms does not consider that combined policies may not

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 0.17 standard deviations. Thus, these two policies are substitutes, in the sense that one particular policy reduces the human capital return to the other policy.

Overall, results 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., 2018). An common result of recent studies is that the impact of child care subsidies on children from low-income families is larger than on the average family (Havnes and Mogstad, 2015; Cornelissen et al., 2018). My 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).

Figure 8 (panel b) 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 8), 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 0.13 standard deviations on average, 13% lower than the treatment effect without a work requirement. In contrast, the work requirement does not cause major changes in the human capital effects of the wage subsidy policy. Taking both policies together, if New Hope had not included a work requirement, the impact on child human capital would have been

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be equal to the reported effects of different policies from different studies. See for example Moffitt (2003) and Moffitt (2016).

14% bigger (0.03 standard deviations). These results provide novel evidence to the research studying the impacts of work requirements (Grogger, 2003; Chan, 2013).[50]

8.2   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.[51] Intuitively, New Hope induced participants to work more; this effect, by itself—holding the rest of inputs constants—has a negative albeit small effect on child human capital. However, by working more individuals have more income, which has a positive effect on child human capital. Further, the program also increased the use of child care, which boosted child human capital accumulation. Mediation analysis quantifies the importance of each of these channels.

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 $\ln \theta_{t+1}^1 - \ln \theta_{t+1}^0 =$

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

[51]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).

$f(\theta_t^1, \tau_t^1, cc_t^1, c_t^1) - f(\theta_t^0, \tau_t^0, cc_t^0, c_t^0)$. This term can be decomposed as

$$
\begin{aligned}
\ln \theta_{t+1}^1 - \ln \theta_{t+1}^0 \quad = \quad & \underbrace{[f(\theta_t^1, \tau_t^1, cc_t^1, c_t^1) - f(\theta_t^1, \tau_t^1, cc_t^1, c_t^0)]}_{\text{explained by consumption}} \\
+ \quad & \underbrace{[f(\theta_t^1, \tau_t^1, cc_t^1, c_t^0) - f(\theta_t^1, \tau_t^1, cc_t^0, c_t^0)]}_{\text{explained by child care}} \\
+ \quad & \underbrace{[f(\theta_t^1, \tau_t^1, cc_t^0, c_t^0) - f(\theta_t^1, \tau_t^0, cc_t^0, c_t^0)]}_{\text{explained by time}} \\
+ \quad & \underbrace{[f(\theta_t^1, \tau_t^0, cc_t^0, c_t^0) - f(\theta_t^0, \tau_t^0, cc_t^0, c_t^0)]}_{\text{explained by self-productivity}}
\end{aligned}
\tag{16}
$$

where each term on the right-hand side identifies the contribution of the corresponding input in explaining the effect of the program.[52]

Table 4: The effects income and child care subsidies on household choices

ATE	(1)	(2)	(3)	(4)	(5)	(6)
Money (US$)	877	1115	857	197	285	1265
Weekly Hours	4.389	4.692	6.807	0.859	2.967	9.224
Child care	0.015	0.234	0.022	0.232	0.154	0.191
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.

Table 4 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 hours worked and consumption by 4.4 hours and 877 dollars, while the child care subsidy rises hours worked and consumption by just 0.9 hours and 197 dollars. In contrast, the impact on child care use is bigger for the child care subsidy (23 percentage points) than for the wage

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[52]Given the linearity of $f(.)$ (see equation 2), the order of the terms in equation (16) does not affect the estimate of the contribution of each input.

subsidy (2 percentage points).

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. Table 4 shows the effects of New Hope policies with work requirements on household behavior. Compared to policies without work requirements, introducing this condition causes only small increases in hours worked and income. What explains this relatively ineffectiveness in producing the desired effects in behavior? 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 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.

I compute the mediation analysis using the structure of my model. I consider the accumulated effect on child human capital for period $t = 2$. I further decompose the term "explained by self-productivity" (which captures the share of the effect of current human capital explained by past changes in this stock) into shares explained by household inputs. Figure 9 illustrated the results for different combination of New Hope policies. For period $t = 2$, child care explains most of the effect of New Hope (62%) while income explains almost all of the rest. The share explained by labor supply is negative but almost negligible. Therefore, the negative effect produced by the rise in labor supply is more than compensated by the positive effects from the increase in child care use and income. This interaction explains the positive impact of New Hope on child human capital up to period $t = 2$.

Figure 9: Mediation analysis: household behavior and the effects of welfare policies on child human capital
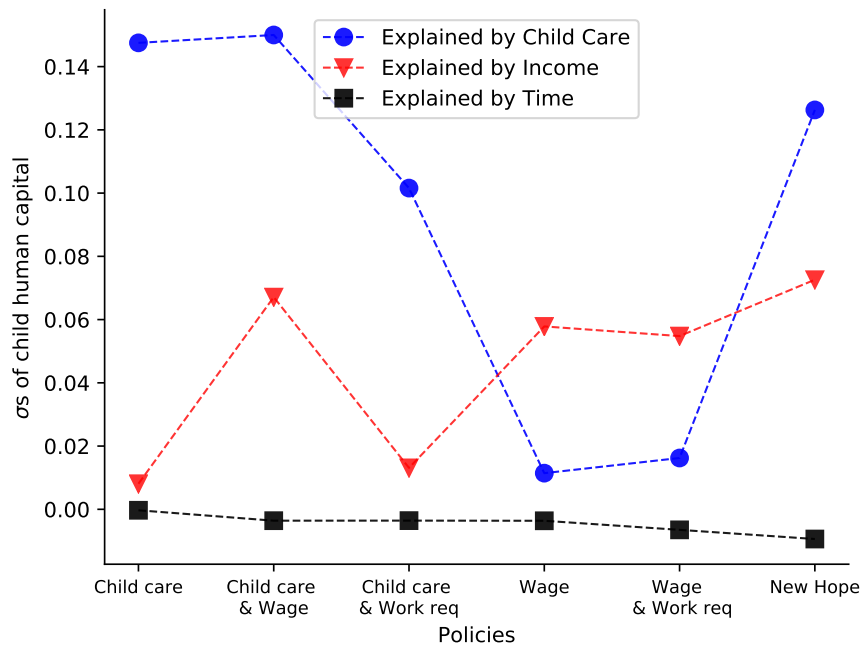
Notes: The figure plots the share of the human capital effects of welfare policies explained by changes in household inputs (time, money, and child care). The policies are abbreviated as "Wage Subsidy (WS)," "Child care Subsidy (CS)," and "Work Requirement (WR)"

The simulated effect of the wage subsidy in isolation emulate the effects of the EITC expansion on child outcomes (see Figure 8). What are the mechanisms explaining the effects of a EITC boost on child outcomes? A first direct channel is the effect that goes 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. Figure 9 shows that, even though most of the effects of the EITC-like wage subsidy are indeed explained by income, a non-trivial part of the treatment effects is accounted by child care.

By comparing the treatment effects of different policy combinations we can explore the mechanisms explaining policy complementarities (or substitutability) in producing child hu-

man capital. Let Y_t^z be a variable of interest under policy regime $Z \in \{WS, WS+CS, CS, \emptyset\}$, where WS is wage subsidy, CS is child care subsidy, and $\emptyset$ is no policy. Let $ATE_Y(Z, Z') = E(Y_t^z - Y_t^{z'})$. We can analyze how policies complement (or substitute each other) in affecting Y_t by comparing $ATE_Y(CS, \emptyset)$ relative to $ATE_Y(CS+WS, WS)$. For example, from Table 4, we can study policy complementarities on income, hours, and child care by substracting columns (1) from (2) (to form $ATE_Y(CS+WS, WS)$) and comparing the result with column (4) (which shows $ATE_Y(CS, \emptyset)$). The effects of a child care subsidy when a wage subsidy is already in place, $ATE_Y(CS+WS, WS)$, equals 238 dollars for income, 0.3 for hours worked, and 0.22 for child care probability. Compared to the effects of a child care subsidy in isolation, $ATE_Y(CS, \emptyset)$, we have larger effects on income and smaller effects on hours worked. By these two channels, by themselves, we should observe larger effects of the combined than the isolated policy, implying that child care and wage are complements. However, the effect of the child care subsidy on child care probability is larger when this policy is implemented in isolation. This last result explain why implementing a child care subsidy on top of the wage subsidy has a lower impact on child human capital than the same policy implemented in isolation.

The mediation analysis reveals why work requirements have negative effects on child human capital. Consider the effect of the child care subsidy with and without a work requirement: the first policy increases child care probability by 23 percentage points while in the second by 15 percentage points. Moreover, the combined policy raises income by 290 dollars versus 197 dollars. Both types of policy bundles have different effects on labor supply, but, as said, time allocation changes (by itself) has a small effect on child human capital. Therefore, 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. Consistently, the mediation analysis 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. Therefore, the lower effect on child care use explains the detrimental effects of the work

requirement on 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.

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 work-based welfare policies impacted child human capital.

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

Two limitations narrow the generability 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

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the New Hope experiment, I cannot analyze general equilibrium effects.[53] 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.

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[53]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 ($\bar{e}$).[54] 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.[55] For two-parents families,

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

[55] 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.[56] 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.[57]

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

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

[57]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.[58] 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.

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[58]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	28.47	28.11	0.36
	[6.88]	[6.33]	(0.55)
Female (%)	100.00	100.00	0.00
	[0.00]	[0.00]	-
African-American, non-Hispanic (%)	56.64	53.85	2.80
	[49.64]	[49.94]	(4.12)
Hispanic (%)	27.62	28.43	-0.81
	[44.79]	[45.18]	(3.72)
White, non-Hispanic (%)	11.54	15.38	-3.85
	[32.00]	[36.14]	(2.83)
Others (%)	4.20	2.34	1.85
	[20.08]	[15.15]	(1.47)
Never married (%)	63.99	63.21	0.78
	[48.09]	[48.30]	(3.99)
Married living w/ spouse (%)	8.39	8.36	0.03
	[27.77]	[27.73]	(2.30)
Married living apart (%)	11.19	11.37	-0.18
	[31.58]	[31.80]	(2.62)
Separated, divorced or widowed (%)	16.43	17.06	-0.62
	[37.12]	[37.68]	(3.09)
Highschool diploma or GED (%)	49.30	44.82	4.48
	[50.08]	[49.81]	(4.13)
Highest grade completed	11.30	11.08	0.22
	[2.02]	[2.05]	(0.17)
$0 (%)	37.76	38.80	-1.03
	[48.56]	[48.81]	(4.03)
$1-999 (%)	17.13	16.05	1.08
	[37.75]	[36.77]	(3.08)
$1,000-4,999 (%)	23.78	23.75	0.03
	[42.65]	[42.62]	(3.53)
$5,000-9,999 (%)	12.59	13.71	-1.12
	[33.23]	[34.46]	(2.80)
$10,000-14,999 (%)	6.29	6.02	0.27
	[24.33]	[23.83]	(1.99)
$15,000 or more (%)	2.45	1.67	0.78
	[15.48]	[12.84]	(1.17)

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

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

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

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

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

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

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

C   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.[59] 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,

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[59]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 6). 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).[60] 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 $(r_{1,t}^k$ and $r_{2,t}^k)$, and the bracket thresholds $(b_{1,t}^k$ and $b_{2,t}^k)$, 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 $(EITC_t^f)$ follows:

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

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

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 4).

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

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

where $\overline{B}$ is the so-called "benefit standard," the maximum amount of welfare an individual is entitled to. Individuals enter the program if $E_t \leq c$. The parameters c and $\overline{B}$ vary by family size and state.[61] 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.

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[60]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.

[61]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:[62]

$$E < 1.3e,$$
$$E_n < e,$$

where net income follows[63]

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

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.[64]

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[62] 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.

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

[64] 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.
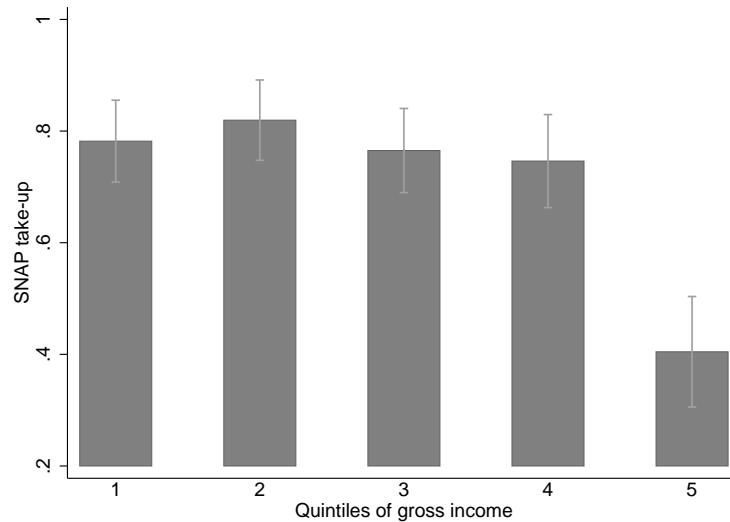
D.4   Take-up rates of AFDC and SNAP

Figure D.1: Take-up rate of AFDC
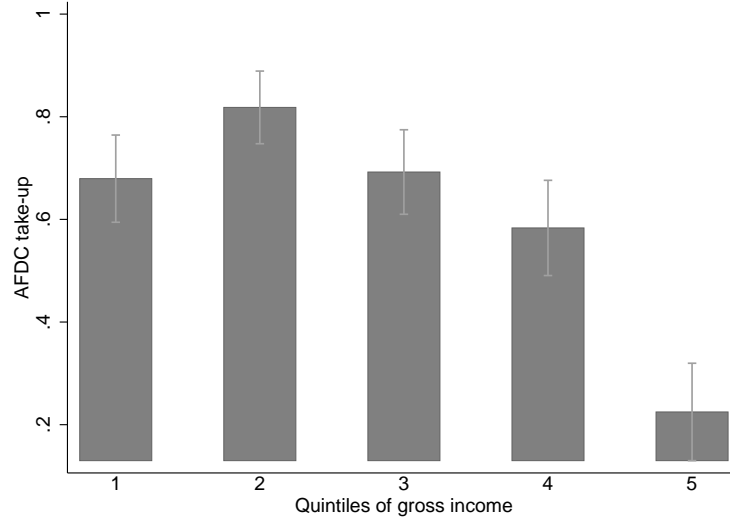
Notes: The figure shows the estimated take-up rate across gross income quintiles during the year of random assignment (1994-1995). The take-up rate is defined as the proportion of eligible families who received a AFDC payment during the year. Gross income corresponds to the sum of quarterly earnings 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) in the context of the dynamic discrete-choice model of this paper. 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.

Let $\boldsymbol{I}_t = \{c_t, \tau_t\}$ be the investment vector. The production function follows

$$\ln \theta_{t+1} = \ln f(\theta_t, \boldsymbol{I}_t) + \mu c c_t \mathbb{I}\{a_t \leq 5\} \tag{E.1}$$

The measures of academic achievement have the following structure:

$$M_t = \ln \theta_t + \epsilon_t^z \tag{E.2}$$

The problem is to identify (E.1) and the parameters of the measurement system (E.2), where the econometrician observes M_t but not θ_t. The following assumptions are needed in order to identify the production function and the distribution of unobserved skills with the available measures.

Assumption 1. *The measurement error, ϵ_t^z, is independent of the errors of the model, and it is uncorrelated across time, for every t.*

This assumption is implied by the fact that individuals in the model based their decisions on θ_t and not M_t (M_t is available only for the analyst).

Assumption 2. $f(.)$ *is such that, for some point (θ_t', c_t', l_t'), $f(\theta_t', c_t', l_t')$ does not depend on an unknown coefficient.*

A related concept, introduced by Agostinelli and Wiswall (2016), states that, for two non-zero vectors (θ_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. This stronger property is called "known location and scale" (KLS). For the purposes of the present model, the KLS assumption is not needed.

I follow Agostinelli and Wiswall (2016) to prove the following Lemma.

Lemma 1. *Suppose that (i) there are two measures M_t and M_{t+1} that follow (E.2) and satisfy Assumption 1; (ii) the joint distribution of human capital and investments $(G(\theta_t, \boldsymbol{I}_t))$ is known or the distribution of measurement error is known $(F(\epsilon_t^z))$; (iii) κ_t from equation (E.2) is known. Then $E(M_{t+1} \mid \ln \theta_t = \overline{\theta}, \ln I_t = \overline{I})$ is known and it is equal to $f\left(e^{\overline{\theta}}, e^{\overline{I}}\right) + \kappa_{t+1}$.*

Proof. Note that we can express $E(M_{t+1} \mid \ln \theta_t = \overline{\theta}, \ln I_t = \overline{I})$ as:

$$E(M_{t+1} \mid \ln \theta_t = \overline{\theta}, \ln I_t = \overline{I}) = \kappa_{t+1} + E\left[\ln \theta_t \mid \ln \theta_t = \overline{\theta}, \ln I_t = \overline{I}\right],$$

give that ϵ_{t+1} is independent of choices. Following Agostinelli and Wiswall (2016), the left-hand side is equivalent to:

$$E(M_{t+1} \mid \ln \theta_t = \overline{\theta}, \ln I_t = \overline{I}) = \int E\left(M_{t+1} \mid M_t = \kappa_t + \overline{\theta} + \epsilon_t^z, \ln I_t = \overline{I}\right) dF(\epsilon_t^z).$$

As $F(\epsilon_t^z)$ and κ_t are known for a given $\overline{\theta}$, $\int E\left(M_{t+1} \mid M_t = \kappa_t + \overline{\theta} + \epsilon_t^z, \ln I_t = \overline{I}\right) dF(\epsilon_t^z)$ is identified. $\qquad\square$

This Lemma says that we can identify the expected value of M_{t+1} conditional on past investments and human capital by having access to a measure M_t. The second condition in this Lemma says that we can either know $G(\theta_t, \boldsymbol{I}_t)$ or $F(\epsilon_t^z)$, since both elements are related through the structure of the measurement system. The proof of Lemma 1 in Agostinelli and Wiswall (2016) makes this assertion implicitly, but I make it explicit here as the main identification proof starts by assuming that $F(\epsilon_t^z)$ is known for some period.

The following lemma adapts Theorem 1 of Agostinelli and Wiswall (2016) to the current set-up.

Lemma 2. *Suppose that (i) the conditions from Lemma 1 hold; (ii) the production function $f(\theta_t, \boldsymbol{I}_t)$ satisfies Assumption 2; (iii)M_{t+1} has full support over the real line. Then $f(\theta_t, \boldsymbol{I}_t)$ is identified over the support of $(\theta_t, \boldsymbol{I}_t)$.*

Proof. Using Lemma 1 and Assumption 2, we can compute $E(M_{t+1} \mid \ln\theta_t = \theta', \ln I_t = I')$ for some known values θ' and I', such that $\ln f(e^{\theta'}, e^{\boldsymbol{I}'})$ is known and it is equal to α: $E(M_{t+1} \mid \ln\theta_t = \overline{\theta}, \ln I_t = \overline{\theta}) = \ln f(e^{\theta'}, e^{\boldsymbol{I}'}) + \kappa_{t+1} = \alpha + \kappa_{t+1}$. Now, let us consider $E(M_{t+1} \mid \ln\theta_t = \overline{\theta}, \ln I_t = \overline{I})$ for some $(\overline{\theta}, \overline{I})$ and take a first difference, yielding

$$E(M_{t+1} \mid \ln\theta_t = \overline{\theta}, \ln I_t = \overline{I}) - E(M_{t+1} \mid \ln\theta_t = \theta', \ln I_t = I') = \ln f(e^{\theta'}, e^{\boldsymbol{I}'}) - \alpha.$$

Since the left-hand side is identified, we can vary $(\overline{\theta}, \overline{I})$ across its support to identify $\ln f(\theta_t, \boldsymbol{I}_t)$. $\qquad\square$

Lemma 2 states that we can identify a production function for a given period, if we know the distribution of current human capital, by exploiting Assumption 2 and with just one additional measure M_{t+1}. The problem nows lies in that $G(\theta_t)$ is not known. Agostinelli and Wiswall (2016) follow a sequential approach to identify a production function that varies in time. They do so by using a standard factor analysis to identify the measurement system and the distribution of initial skills. This is the starting point to identify a production function in $t = 1$. Given this production function, one can also identify the distribution of human capital in period $t = 1$, and then subsequently use their Theorem 1 to sequentially identify the production function for all t.

One major drawback in this present case is that there are no baseline measures of academic achievement. Thus, a direct identification exploiting the Agostinelli and Wiswall approach cannot be pursued. Furthermore, we only have available measures for three, but not consecutive periods, which further complicates identification. The following proposition adapts the identification argument to the context of this paper and proves that identification is still achieved.

Proposition 1. *Let M_t, for $t = 2$ and $t = 5$ two noisy measures of child human capital that follow equation (E.2) and meet Assumption 1. Consider a forward-looking agent that behaves as equation (12) (the dynamic representation of the individual's maximization problem) dictates. Then the production function of human capital (equation 2) and the distribution of human capital $G(\theta_t)$, for all t, are identified under the following conditions.*

i. The initial marginal distribution of human capital $G(\theta_0)$ is known;

ii. The measurement error distribution in period $t = 2$ is known: $F(\epsilon_2^z) \equiv F_{\epsilon_z^2}$.

ii. $E(\ln \theta_2) = 0$ (normalization).

Proof. Consider $E(M_5 \mid \ln \theta_4, \ln I_4)$. Since we do not have M_4 this object is not identified. Nonetheless, we can compute $E(M_5 \mid \ln \theta_2, \ln I_4, \ln I_3, \ln I_2)$ by applying Lemma 1 to the pair of measures M_5 and M_2 by recursively using the production function (which does not vary in time):

$$
\begin{aligned}
\ln \theta_5 &= \ln f(\theta_4, I_4) \\
&= \ln f\left(\ln f\left(\theta_3, I_3\right), I_4\right) \\
&= \ln f\left(\ln f\left(\ln f(\theta_2, I_2), I_3\right), I_4\right) \\
&\equiv g(\theta_2, I_2, I_3, I_4),
\end{aligned}
$$

thus

$$
E(M_5 \mid \ln \theta_2, \ln I_4, \ln I_3, \ln I_2) = g(\theta_2, I_2, I_3, I_4) + \kappa_5.
$$

Since $E(\ln f(\theta_t, I_t)) = 0$, for $t = 2$, κ_2 is identified as $E(M_2 \mid cc_t = 0) = \kappa_2$. Furthermore, given that $f(\theta_t, I_t)$ from equation (2) meets Assumption (2), so is $g(\theta_2, I_2, I_3, I_4)$. As the conditions for Lemma (2) are met, $g(\theta_2, I_2, I_3, I_4)$ is identified over the support of $(\theta_2, I_2, I_3, I_4)$, by using the property laid out in Assumption (2) for a point (θ', I', I', I'), such that $f(\theta', I')$ is known—and so is $g(\theta', I', I', I')$. Thus, as $g(\theta_2, I_2, I_3, I_4)$ is identified, $f(\theta_4, I_4)$ is identified as well.

The identification of the rest of the elements in the measurement system and production function follow after establishing the identification of $f(.)$. As $f(.)$ is identified and the investment vector is observed, the joint distribution of $G(\theta_5, I_5)$ is also identified. Thus, we can recover κ_5 by computing $E(M_5 \mid cc_5 = 0) - E(\ln f(\theta_5, I_t)) = \kappa_5$. From here, the child care total factor productivity (μ from equation (E.1)) is also identified by conditioning on $cc_t = 1$: $E(M_5 \mid \ln \theta_5, \ln I_4, \ln I_3, \ln I_2, cc_5 = 1) - \kappa_5 - g(\theta_2, I_2, I_3, I_4) = \mu$. $\qquad \square$

Proposition 1 establishes the main identification result. The conditions for identification are stronger than what it is usually assumed in standard factor analyses. Nonetheless, these conditions are necessary, given the lack of baseline data M_0.

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

- $Corr(incomepc, ssrs)$. Income_pc here is income divided by the number of children (I'm not considering child care payments here).

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	0.523	0.516	0.030
$Pr(\text{part-time}_t \mid RA = 0)$, $t = 0$	0.263	0.286	0.012
$Pr(\text{full-time}_t \mid RA = 0)$, $t = 0$	0.458	0.466	0.015
B. Individual: $log(wage_t) = X_t'\beta + \epsilon_t$			
Coefficient on high school dummy	0.231	0.236	0.069
Coefficient on time trend	0.081	0.086	0.010
Constant	1.610	1.594	0.069
σ^2	0.421	0.379	0.085
AR(1) shock (ρ)	0.307	0.287	0.083
C. Spouse: $log(wage_t) = X_t'\beta + \epsilon_t$ and employment			
High school dummy	0.088	0.101	0.147
Constant	7.184	7.205	0.101
σ^2	0.248	0.261	0.066
Employment probit	0.182	0.186	0.027
D. SSRS and household choices			
$Corr[SSRS_2, SSRS_5]$	0.479	0.483	0.056
$Corr[\text{consumption}_1, SSRS_2]$	0.028	0.019	0.035
$Corr[\text{time}_1, SSRS_2]$	0.035	0.032	0.034
$E(SSRS \mid cc = 1) - E(SSRS \mid cc = 0)$	0.275	0.277	0.173
$Var(SSRS_2)$	0.880	0.909	0.051
$Var(SSRS_5)$	0.982	1.033	0.047
$Corr(SSRS_2, \ln w_0)$	0.018	0.004	0.062

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

G.3 Local identification from targeted moments

Figure G.1: Target moments locally identify structural parameters: utility function
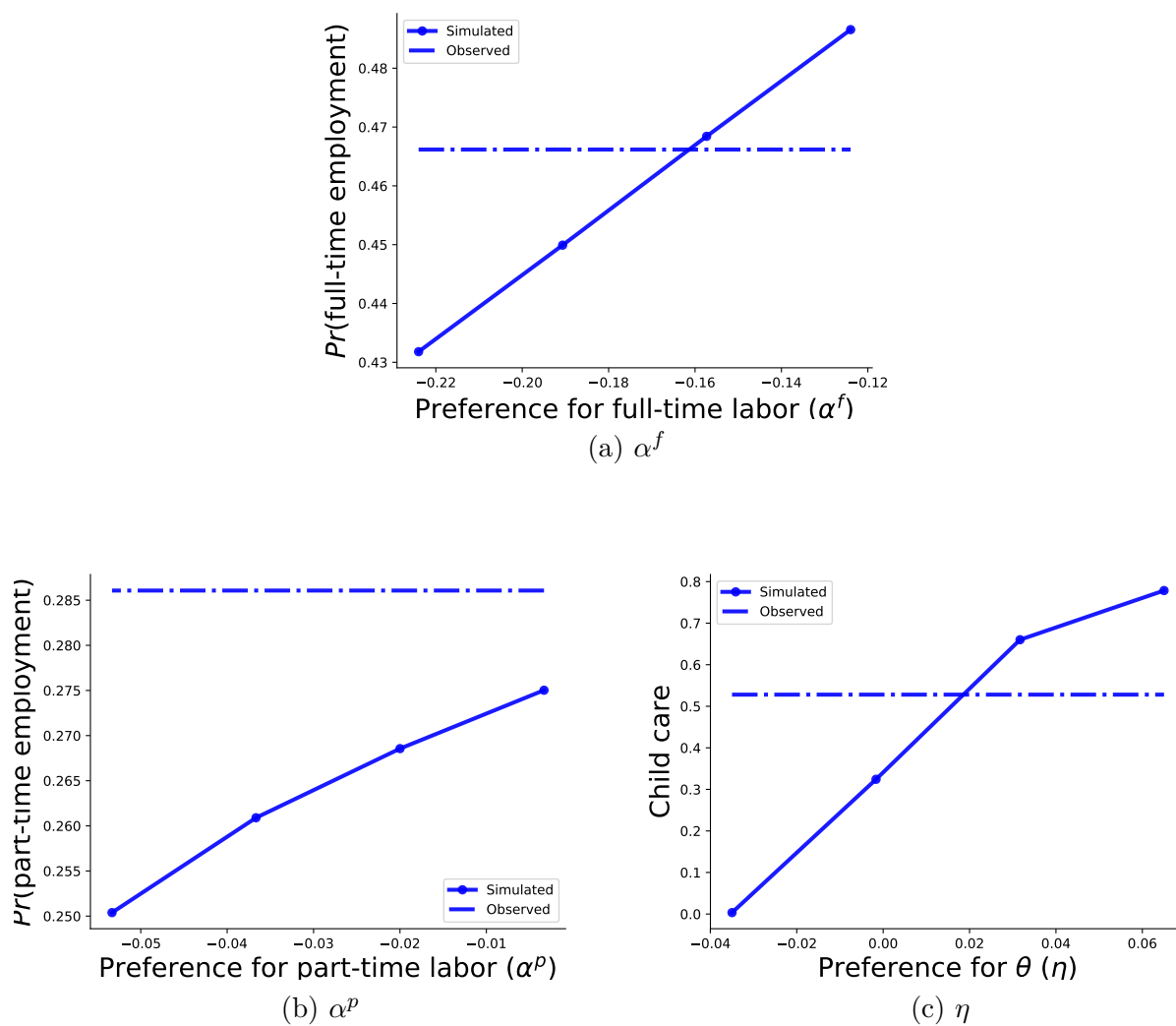
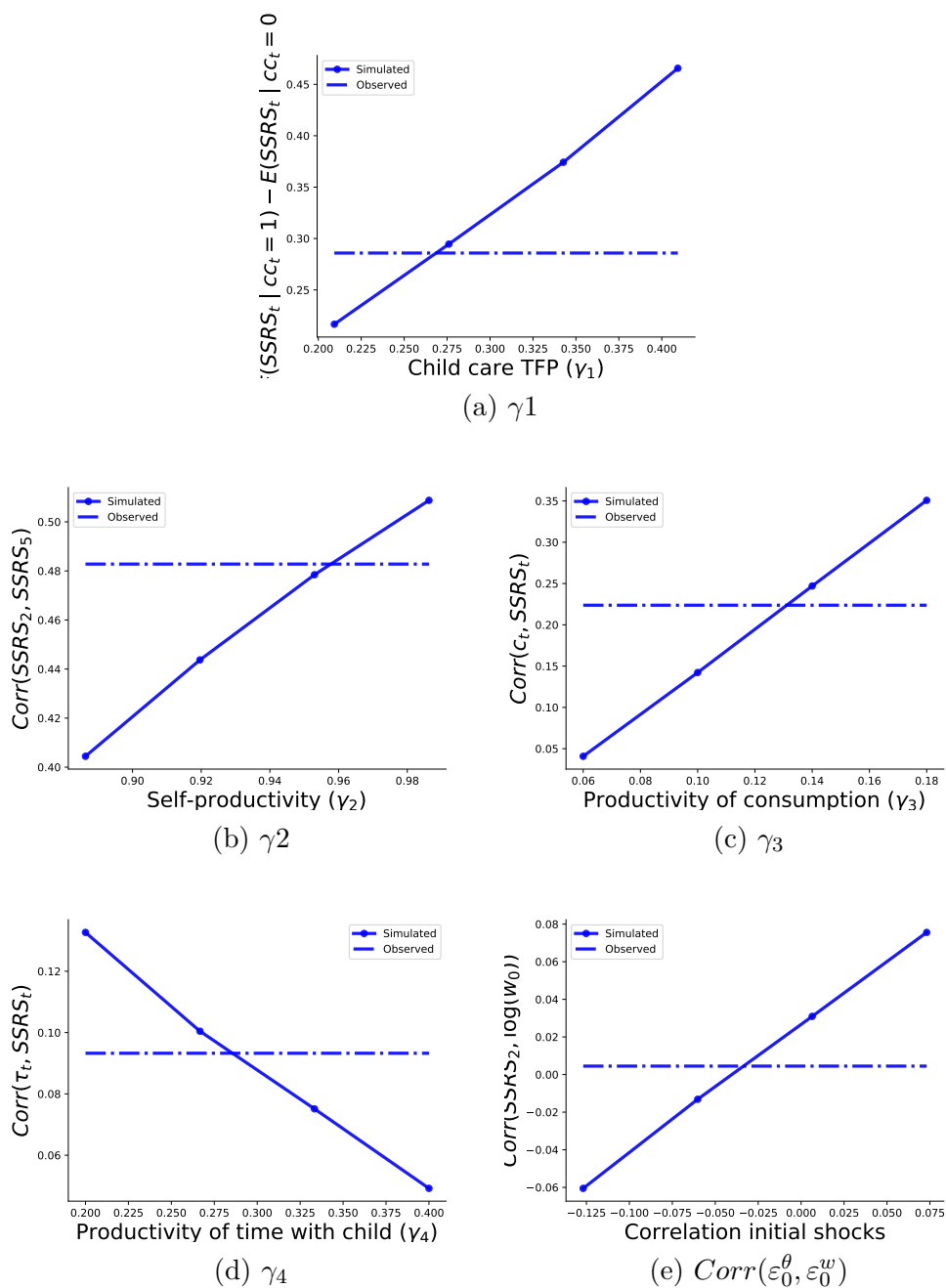(a) α^f

(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
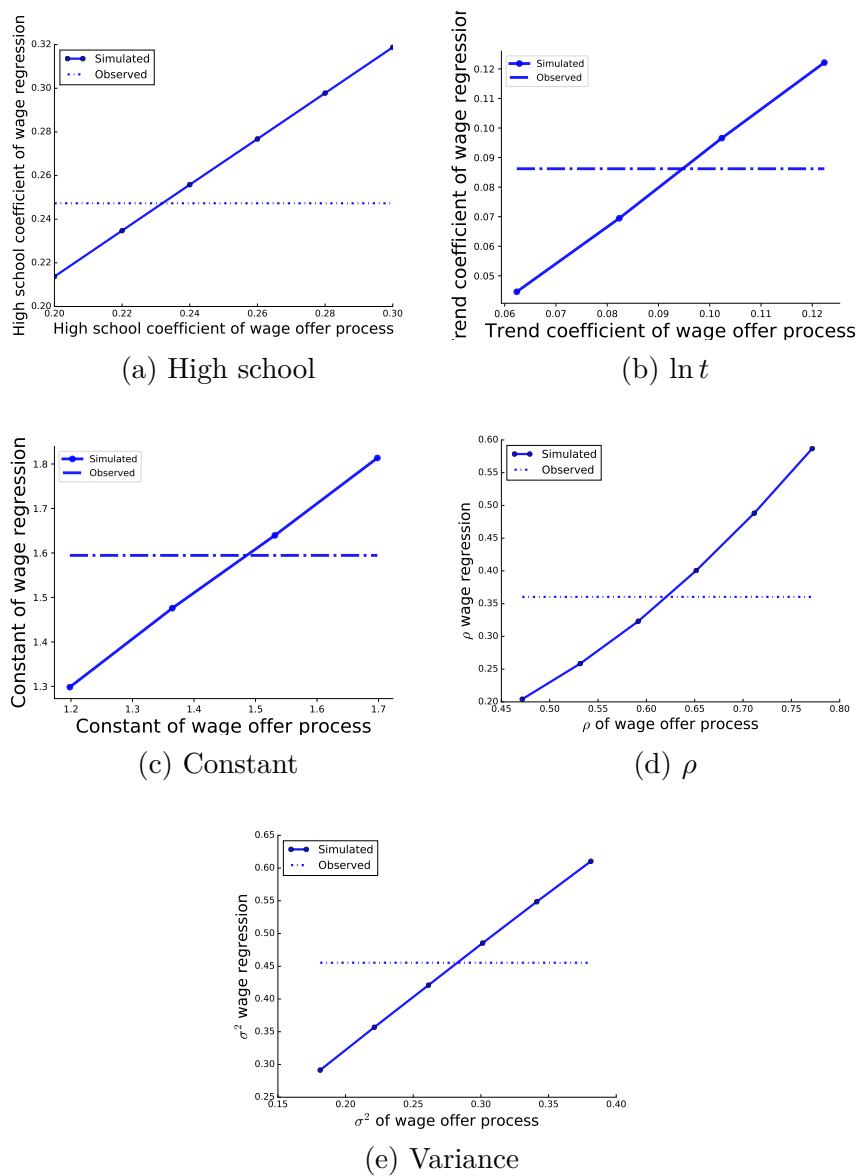
(a) High school

(b) $\ln t$

(c) Constant

(d) ρ

(e) 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) $\gamma 1$

(b) $\gamma 2$

(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.