IMPROVING CHILD OUTCOMES THROUGH WELFARE REFORM

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Abstract

This paper studies the design of antipoverty programs in the United States and their impact on child development, maternal welfare, and labor supply. I formalize and estimate a model in which maternal investments of time and money determine child outcomes through a technology of skill formation. Mothers choose these investments, their labor supply, and their program participation subject to constraints on their time and budget. I use this structure to answer important policy questions regarding the design and delivery of income supports to poor families. Properties of the model's solution facilitate transparent identification of key structural parameters, which in turn informs the chosen estimation procedure. Estimates of the model indicate that inequality in economic resources explains a relatively small portion of the variance in skill outcomes. However, this result does not obviate the role played by transfer programs in bolstering the development of children who are threatened by poverty. I find that there are significant returns to providing additional support to the poorest families in the sample. For example, a cost-neutral policy reform, based on a minimum guaranteed income standard, can significantly improve the cognitive and behavioral skills of the most economically disadvantaged children. When associated with high school graduation, the induced change in skills lifts the probability of graduation by 2.9 percentage points for children in the bottom 10 percent of the income distribution. Finally, estimates unveil a crucial role played by heterogeneity across mothers. First, heterogeneity in maternal preferences and investment productivities explains over 90% of the observed variance in skill outcomes. Second, while some mothers respond beneficially to the provision of additional labor supply incentives, those with lower wages and a greater preference for leisure do not. Since these mothers sit at the bottom of the income distribution, this introduces an equity-efficiency trade-off for policymakers.

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Introduction

The main ambition of this paper is to establish guidelines for the appropriate size and shape of government antipoverty programs. There are strong ethical and pragmatic arguments for providing income supports to poor families: econonomic disadvantage may malform human capital in childhood, limiting adult socioeconomic outcomes and exacerbating the transmission of inequality between generations. However to date, little is known about the effect of program design choices as they pertain to child outcomes and maternal welfare.

I make progress here on this issue, by estimating a model of maternal labor supply, program participation, and child development, establishing trade-offs and possibilities for improving the allocation of public funds. Three major programs exist in the United States with the express purpose of alleviating poverty: (1) the Supplemental Nutritional Assistance Program (SNAP); (2) Temporary Assistance for Needy Families (TANF); and (3) the Earned Income Tax Credit (EITC). These policies show great variation both between and within themselves over time in terms of their *conditionality*: in particular the extent to which their benefits are tied to labor force participation. Given this, it is critical that policy-makers understand the wide-ranging impacts of this program feature. While many papers have studied the effects of changes in these policies on demographic outcomes, this paper is the first to perform an empirical, normative analysis of program design, assessing properties of efficiency and progressivity. Furthermore, it is the first to conduct a careful analysis of program effects on child development outcomes. I find that improvements in child skills can be achieved through alternative programs that cost no more than the current suite of publically funded initiatives. There are, in particular, large gains in child scores when program changes are designed to target children at the bottom of the income distribution. For example, a reform based on a minimum income standard, which patches a hole in the current safety net, increases the rate of high school graduation for children in the lowest income decile by 2.9 percentage points.

Although these policies exist in part to protect children from the negative consequences of economic deprivation, this is not their sole purpose. They also act as an important source of insurance and support for the single mothers in our sample, and a wider population of individuals facing economic disadvantage. Since the effects of different program parameters are not perfectly aligned across these dimensions of impacts, policymakers face import trade-offs. I will show, using the estimated model, that these trade-offs are non-trivial: policies that maximize child outcomes do not maximize maternal welfare. This highlights an important contribution of this work, since it offers counterfactual analysis of a more complete portfolio of socioeconomic outcomes.

I perform this analysis using a model in which demographic variables are determined by constrained, economic choices, that are fully articulated in a rich array of welfare policy environments. I estimate the model using longitudinal data on maternal labor supply, time use, earnings, welfare participation, and child outcomes. I then use these estimates to simulate decisions and child outcomes under counterfactual policy arrangements. My estimates, combined with these experiments, produce an important set of findings.

There are significant returns, both in maternal well-being and child outcomes, to targeting program changes towards mothers at the bottom of the income distribution. Examination of the data and simulations from baseline reveal that many mothers do not participate in welfare, and do not capitalize on the work rewards offered by the EITC. In addition, since the EITC pays a percentage return on earnings, it rewards mothers with lower wages less generously for the same amount of labor. For these reasons, the current system of supports is not maximally progressive. Since recent trends in program design have shifted funds away from welfare programs and towards work incentives, it is critical that we understand both the average and the distributional impacts of these changes. By uncovering fundamental population heterogeneity, the model provides an opportunity for projections of this kind.

Heterogeneity in parental preferences and productivity explains upwards of 90% of the variance in child outcomes, suggesting that eliminating economic inequality will not make a large impact on overall inequality in skill development. However, both time and money are found to be critical inputs in skill production. Thus, when current policies are reconfigured to target the most needy families in the sample, this results in appreciable human capital gains. This study highlights the fact that there are potentially important social returns to fine-tuning and strengthening the social safety net.

The problem of how to design income supports can be defined over two key dimensions. First, how fundamentally generous should these programs be? Second, conditional on size, how forcefully should these policies encourage labor supply and self-sufficiency? Some programs, such as the *Earned Income Tax Credit* (EITC), reward labor supply by phasing in the transfer as earnings increase. The EITC, in this fashion, acts as a negative income tax. Other programs may discourage labor supply by phasing out a baseline transfer as earnings increase. This is true of both incarnations of welfare in The United States: *Aid to Families with Dependant Children* (AFDC), and *Temporary Assistance for Needy Families* (TANF), as well as the latter part of the EITC transfer schedule. The phase-out rate of these transfers determines the severity at which additional earnings are effectively taxed. Programs that rapidly phase out transfers with earnings impose high rates of marginal income taxation, which strongly discourages labor supply.

Historically, efforts to alleviate poverty in the U.S. have varied chiefly in these two dimensions. Recent decades have seen a concerted policy shift towards programs that encourage self-sufficiency and discourage dependance on government support. First, the 1990s saw a significant expansion in the EITC, particularly in the period between 1993 and 1995. Second, in 1996, the *Personal Responsibility and Work Opportunity Reconciliation Act* (PRWORA) was signed into law. This act affected a transition in 1997 from the former welfare program *Aid to Families with Dependant Children* (AFDC) to a new program: *Temporary Assistance for Needy Families* (TANF). Three aspects of the reform combined to encourage labor force participation among welfare recipients. First, entitlements to TANF are limited to a 60 month time limit for participants[1]. Second, recipients are required to spend 20 hours a week in work or work-related activities. Failure to meet this requirement is punishable by sanctions. Third, many states restructured their benefit calculation formulae to reduce the effective marginal tax rate on earnings. This series of institutional changes was successful in shifting a sizeable number of participants off welfare rolls and into the labor force (Hoynes, 1996; Grogger, 2002, 2003; Chetty et al., 2013). I fit the model to data taken from a period that encompasses the timing of these policy changes. This provides a valuable opportunity to study the effects of variation in policy arrangements on key variables of interest that interact causally in the model.

In the model, child outcomes are determined by maternal investments of time and money, which enter into a skill production function. Skill formation in the model is both *dynamic*, in that human capital at maturity is determined over several periods in which current skills combine with investments to beget future skills, and *multidimensional*, in that it incorporates an array of both cognitive and socioemotional abilities. This model of skill formation joins work at the frontier of research on human capital development, which suggests that both these features are essential (Cunha et al., 2010; Almlund et al., 2011; Heckman et al., 2006).

If child development depends on the availability of both time and money, as it does in this model, then the design choices of governments with respect to antipoverty programs has important implications for this process. I study the problem of program design through this lens, evaluating alternative policies of equivalent size to the suite of initiatives in the U.S. with different degrees of labor supply incentivization. These questions are of critical importance to society and to broader discussions of policy. Prior research suggests that skills and capabilities (which I sometimes refer to in this paper as human capital) are most malleable in childhood (Cunha et al., 2010), and that these skills wield considerable influence over important socioeconomic outcomes [2]. The extent to which human capital can be shaped by policies, and the extent to which this malleability is concentrated in childhood, has strong implications for the optimal timing and design of social programs. In addition, these insights provide a sense of possibility when faced with the problem of socioeconomic inequality: the nature of skill formation in childhood frees policymakers from the constraints of traditional equity-efficiency tradeoffs (Cunha and Heckman, 2007).

To date, many empirical studies of public investment in children have validated this theoretical perspective. Analyses of experimental Early Childhood Education (ECE) initiatives have shown very high returns on initial program costs (Heckman et al., 2010), and that much of these gains can be explained by the change in skills induced by the program (Heckman et al., 2013). The results

[1]These time limits apply only to the block grants awarded to the States by Federal Government. States can, if they choose, independantly fund support beyond the time limit.

[2]Some primary examples include: high school and college completion, earnings, health, and prosocial behaviors.

on the impacts of early childhood investment suggest a pragmatic case both for improving and expanding current programs. At the very least, they encourage a particular prior that improving such programs can bring potentially large gains in outcomes.

The structure of the model I develop allows, in principle, for many different potential answers to the questions of best policy design. My theory proposes that welfare policies affect development because they shape two important economic constraints: the availability of time and money. Thus, my results will hinge on the absolute and relative importance of these factors in producing child outcomes. This amounts to estimating the human capital production function of children, which is the first major input into subsequent policy analysis. On its own, this object is not sufficient to analyze counterfactuals. We need, in addition, the ability to model and predict parental responses to policy changes. This is enabled by specifying parental preferences over relevant outcomes and adapting revealed preference arguments to identify them from data. Both these components - the production technology, and parental preferences - are specified so that they can be statistically identified in a transparent way from the available data. The model then, in addition to providing theoretical insights into the policy design problem, provides a mapping from historical data to alternative simulations, which lies at the heart of this paper's analysis.

The causal relationship between economic resources and child outcomes can be difficult to infer from the data, since it is likely that unobservable family characteristics determine both family income and child outcomes. To negotiate this issue, several studies have used natural experimental variation in family budgets, either through welfare programs (Duncan et al., 2011) or the EITC (Dahl and Lochner, 2012; Chetty et al., 2011), to estimate a fairly consistent effect size: $1,000 in additional annual income can increase test scores by between 6 and 9 percent of a standard deviation. Additional work suggests that these income effects are not limited to test scores, producing long-term effects in outcomes also (Loken et al., 2012; Hoynes et al., 2014). [3] While some researchers have expressed cynicism about the use of transfers to boost child outcomes (Heckman and Mosso, 2014), these results suggest that economic resources have some role to play in the development process. Although useful and critical, the empirical design of these studies does not permit fully realized policy counterfactuals.

We can use the model as a lens through which to interpret these estimates. One insight is that the same combination of production and preference parameters can easily produce different impacts, depending on the policy variation and research design that is used to estimate them. In particular, a $1,000 increase in annual income will have variable effects depending on the changes in labor supply that each policy induces. Furthermore, while each policy might produce identical effects on cognitive test scores, they may affect other skills differently. Since the formation of skills is dynamic and complementary, there could be stark differences between contemporaneous and long-term impacts.

[3] This finding is not unanimous, however. See Cesarini et al. (2015) for an important example.

The structure of the model can be described in more detail as follows. Mothers have preferences defined over the outcomes of their children, their private consumption, and private leisure. They can improve the outcomes of their children by investing either time or money, but are limited in terms of two key resource constraints: their annual budget (the sum of their earnings, non-labor income, and government transfers) and the number of hours available in the period. Thus, investments in children must be made at the expense of private consumption and leisure. Labor supply acts as a means for agents to expand their budgets at the expense of time. Mothers choose the amount of labor they supply to the market, as well as their participation in government programs. These decision variables, along with the mother's wage, and the relevant government policy in each time period determines the household budget. The decision problem faced by a mother is dynamic, since she must weigh the future return to skills (which develop over time) against her current consumption and leisure. These features of the model build on work by Del Boca, Flinn, and Wiswall (2014), which itself follows in the tradition of Becker and Lewis (1973) and Becker and Tomes (1976).

I extend the modelling framework of Del Boca et al. (2014) in several meaningful ways. First, I adopt a multidimensional skill technology, which broadens the policy implications and importance of the study, since behavioral traits are influential in shaping many life-cycle outcomes (Heckman et al., 2006). Furthermore, theory and evidence suggest that such skills are crucial in the development of future skills (Cunha and Heckman, 2007; Cunha et al., 2010). I also pursue a different approach to identification of the production technology which, in combination with the fact that I estimate the model on a different population of children, allows for new empirical insights on the nature of human capital formation in childhood. The empirical methodology I adopt here, which mediates the developmental effects of programs through their effect on family income and total maternal hours, resembles the approach taken by Bernal (2008) and Bernal and Keane (2010), yet differs markedly in terms of the theoretical foundations for this approach and its analytical focus.

To properly analyze the problems and populations of this paper, my model takes extra precision in reflecting the economic and policy environment that corresponds to each available year in the data. Mothers must elect to participate in welfare, and are subject to eligibility requirements and benefit calculations that approximate the salient policies from the year in which the data is taken. In addition, I incorporate the introduction of work requirements and time limits that were brought on by the reform act. This aspect of the problem bears similarity to the empirical and modeling approaches taken by Hoynes (1996), Keane and Wolpin (2002), and Swann (2005). In addition to accurately capturing the welfare environment for each year and family in the sample, I ensure that the EITC for each family's earnings is calculated exactly according to its historical parameters. To date, Chan (2013) is the only paper that takes an equally thorough environmental approach to modeling the labor supply and welfare participation decisions of single mothers. An additional advantage of explicitly modeling the policy changes that take places through the sample period is that I can exploit exogenous program changes to aid in identification of the model.

Although this paper focuses on questions of general policy design, the historical setting and data employed in estimation permit additional insights into the effect of welfare reforms. In particular, while the post-reform era has seen modest increases in family income, this has arrived in hand with increases in labor force participation and stricter eligibility requirements. The likely impact of this structural change depends on the estimated parameters of the production function, which determine the quantitative importance of time and money. By fitting the model to data, I derive predictions for both the average and distributional impacts of welfare reform. Work by Bernal and Keane (2010; 2011) suggests that there are potential negative impacts on child test scores when mothers join the labor force and use childcare. This of course may be countered by the positive impacts of additional income in the family budget, or by future growth in human capital induced by labor force participation (Blundell et al., 2013). Fang and Silverman (2009) argue that this may be one key benefit of imposing time limits on welfare, since it provides a credible commitment for time-inconsistent agents to join the labor force.

I estimate the model using data on single mothers from the *Panel Study of Income Dynamics* (PSID) and its *Child Development Supplement* (CDS). The CDS provides, in three waves (1997, 2002, 2007), important measures of development outcomes for selected children of PSID families. I study the formation of two measures of cognitive skill (verbal and math) and two measures of behavioral problems (externalizing and internalizing) reflected by scales taken from this supplement. Many studies, including the ones mentioned here, rely on evaluating test score impacts in terms of their relative scale. I exploit the longitudinal component of the PSID to tie each score to a human capital outcome of significant interest: high school graduation. This approach, known as "anchoring", gives a more interpretable scale to estimates of the skill production function (Cunha and Heckman, 2008; Cunha et al., 2010). In addition, when considering the effect of policy counterfactuals, I simulate counterfactual graduation probabilities by estimating a model of high school graduation that depends on all four skills.

This paper offers progress on a number of high level questions. First, what is the causal importance of economic disadvantage in childhood in determining life-cycle outcomes? Second, how do current anti-poverty measures remediate environments for disadvantaged children? Finally, what is the scope (if any) for potential improvements that can be made by adjustments to these programs? In my analysis, I find evidence of important channels for both monetary and maternal time invesment to shape the outcomes of children through each stage of their development. However, the impacts of direct transfers to all sample families are modest: an annual lump sum payment of $1,000 to every family with a child younger than 17 produces positive but small test score gains. When skill outcomes are linked to the probability of graduating from high school, this initiative produces an increase in the graduation rate of 0.44% points. Most importantly however, there are large skill returns to expanding program coverage to poor, working mothers. When I impose a minimum income standard on all families in the sample, I find that the rate of high school graduation is boosted by 2.9% points for children in the poorest 10% of families.

This paper is the first to conduct policy analysis of government income supports and child development using a quantitative, behavioral model. In addition, it contributes a range of methodological and theoretical insights into how government policies can affect child outcomes and how such effects can be identified from data. Finally, I provide some important implications for current federal policies, showing that there are potentially large gains to be made by targeting programs towards the poorest families in the sample. The rest of the paper proceeds as follows. In Section 2 I describe the data used to estimate my model of parental investment, labor supply, and program participation. In addition, I identify important temporal trends in the data that have implications for future changes in policy. In Section 3, I introduce the model, presenting details and properties of its solution. Section 4 provides details regarding the estimation procedure I employ, as well as a discussion of identification. In Section 5 I use these estimated parameters to conduct counterfactual policy analyses, leading to conclusions in Section 6.

Data

To answer the empirical and policy questions outlined in Section 1, I use data from the *Panel Survey of Income Dynamics* (PSID) and its *Child Development Supplement*. The PSID is a dynastic, longitudinal survey taken annually from 1968 to 1997, and biennially since 1997. It collects important information on a range of economic and demographic indicators. The CDS consists of three waves, collected in 1997, 2002 and 2007. Any child in a PSID family between the ages of 0 and 12 at the time of the 1997 survey was considered eligible. These surveys contain a broad array of developmental scores in cognitive and socioemotional outcomes as well as information on the home environment of the child. One important feature of the survey is the availability of time use data, which is collected by the participants' completion of time diaries. I provide further details below.

Description of Variables and Sample Selection

From the PSID survey I collect data on mothers' labor supply, labor income, total family income, welfare receipt and some demographic variables. The CDS is comprised of several questionnaires. I use two in particular: the child interview and the *primary caregiver* (PCG) interview. From the child interviews, I use measures of cognitive ability as reflected by a battery of test scores. From the primary caregiver interview I use a number of behavioral scales constructed by the caregiver's answers to a series of questions regarding the child's behavior. In addition to this, the PCG completes a passage comprehension test, and a number of items from which scales on the caregiver's self-esteem (Rosenberg, 1986) and self-efficacy (Pearlin, Lieberman, Menaghan & Mullan, 1981) can be constructed. When the PCG is identified as the mother of the child, I collect these scores also.

To measure child attributes, I utilize two measures of cognitive ability and two measures of behavioral traits. For cognitive ability, I use the Letter-Word (LW) and Applied Problems (AP) modules of the Woodcock-Johnson Aptitude test. For socioemotional or "non-cognitive" abilities, I use constructed scales that measure *externalizing* and *internalizing* behavioral problems. This gives, in total, four measures of child attributes that we use to track human capital outcomes. In the next section, I explore how each measure is related to adult outcomes, as proxied by high school graduation.

Finally, the CDS asks participant children to fill out a "time diary". This portion of the survey requires participants to record a detailed, minute by minute timeline of their activities for two days of the week: one random weekday and one random day of the weekend. Activities were subsequently coded at a fine level of detail. When necessary, children are assisted in completion of the time diary by the PCG. These diaries provide a unique snapshot into the daily life of the child. From this data I construct a measure of maternal time investment by taking a weighted sum[4] of the total hours of time use in which the mother is recorded as actively participating in each diary activity.

Since much of the focus of the antipoverty programs considered here is on single mothers, sample restrictions are made to look more closely at this subpopulation. Since family structure in the data is quite dynamic and tends to fluctuate, a stand must be taken on how to restrict the sample. Following Fang and Silverman (2009), I restrict attention to mothers of CDS children who never marry. Making this restriction leaves 368 mothers and 528 children. Of these mothers, 38% have not completed high school, 57% have high school diplomas, and 5% have college degrees. The mean of annual total household income in the sample is $21,371, while median annual income is nearly $16,000. Finally, 60% of these mothers have reported welfare use at least once, while 24% have reported welfare participation for at least 5 years.

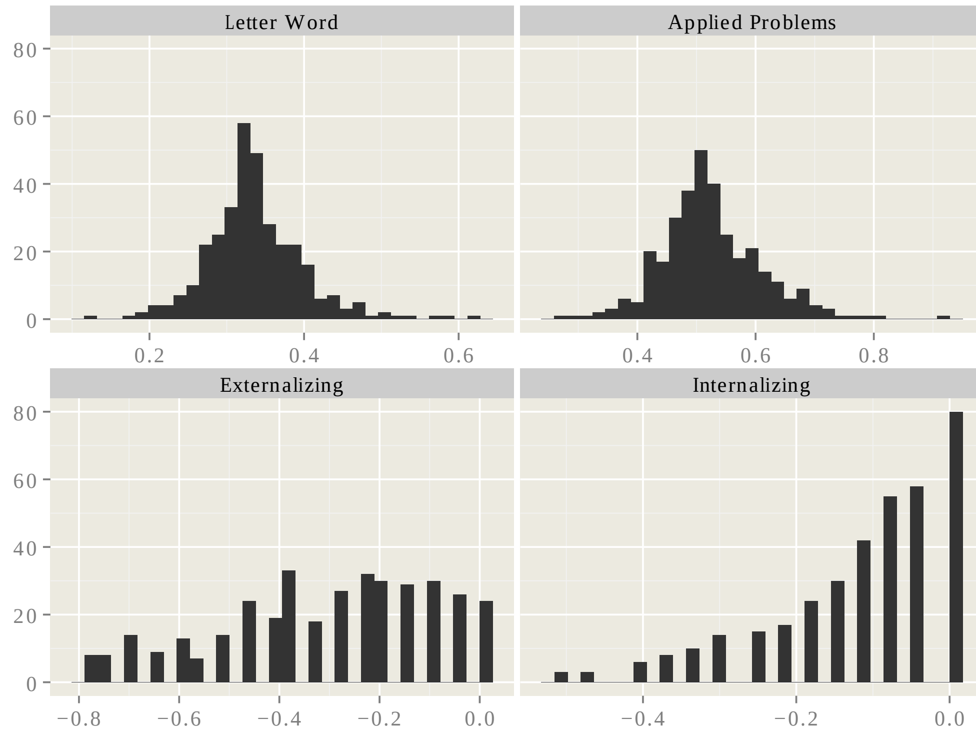
Anchoring Test Scores

In order to give some weight to the scale of cognitive and behavioral scores, I next inspect how each score is associated with the probability of high school graduation. To do this, I estimate a series of linear probability models to give each skill outcome an interpretable scale. That is, for each skill k, if $\tilde{\theta}_{i,k}$ is the raw score of skill k for child i, I estimate the model:

$$HSG_i = \mathbf{1}\{\text{const}_k + \tilde{\theta}_{i,k}\beta_{HSG,k} - U_i \geq 0\}, \qquad U_i \sim \text{unif}[0,1] \tag{2.1}$$

[4] $\frac{5}{7}$ for the weekday, and $\frac{2}{7}$ for the weekend

Figure 2.1: Distribution of Anchored Test Scores



Note: This figure shows the distribution of child test scores, anchored by their association with high school graduation, as described in equation (2.1). Moving clockwise from the upper left panel, we see the distributions of Letter-Word scores (LW), Applied Problems scores (AP), Externalizing Behaviors (BE) and Internalizing Behaviors (BN).

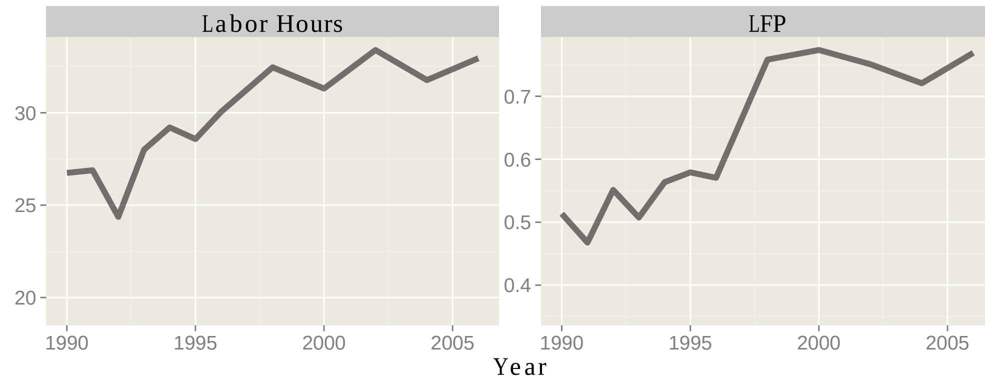
Thus, I re-weight each raw score to get $\theta_{i,k} = \beta_{HSG,k}\tilde{\theta}_{i,k}$, so each skill has been "anchored" in the language of Cunha and Heckman (2008), to the probability of high school graduation. Estimates are presented in Table A.1. In Figure 2.1 I plot histograms of the scaled test scores. Importantly, we can see plenty of meaningful variation in skill measures once associated with an adult outcome of interest.

Trends in Labor Supply, Welfare, and Family Income

In this section I document some of the temporal and cross-sectional patterns of the dataset I employ in this project. I am particularly interested in documenting the effect of changes in the insitutional and economic environment faced by mothers through the 1990s on their income, labor supply, and program participation. In addition to these patterns, it is important to examine the role played by welfare in the poorest households. This will provide insight into potential areas for improvement in policy design.

As discussed in Section 1, the 1990s saw significant and relevant changes to the economic environment faced by families with children. Figure 2.2 shows trends in labor supply during

Figure 2.2: Trends in the rate of Labor Force Participation and hours of labor supply of CDS Mothers



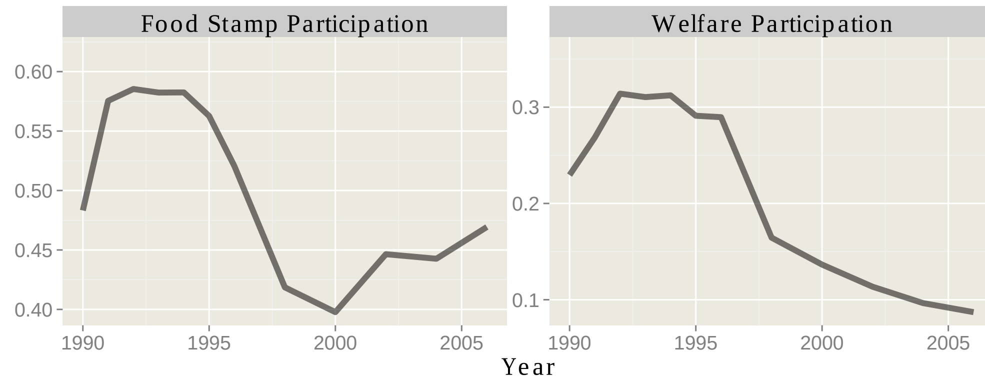
Note: This figure shows trends in the weekly hours of labor supplied to the market, conditional on labor force participation (left) and the rate of labor force participation among CDS mothers in the sample (right).

this time period. I plot the rate of labor force participation (LFP) and, conditional on labor force participation, the mean weekly hours spent at work by mothers in the sample. This plot demonstrates that, through this time, more mothers joined the labor force and, conditional on doing so, supplied more hours of labor to the market. In technical terms, we see an increase in labor supply at both the *extensive* and *intensive* margins. This trend is likely due to a combination of the following effects: (1) the mean age of children in the sample is increasing, reducing the marginal importance of time at home; (2) an increase in the return to labor through rising wages; and (3) an increase in the returns to labor from expansion of the EITC and the switch from AFDC to TANF.

Mirroring this trend, Figure 2.3 shows a commensurate decline in the reliance on and generosity of welfare. There are two likely sources of this change. First, if mothers are earning more by expanding their labor supply, this decreases the rate of eligibility for welfare and, conditional on eligibility, also decreases receipt in welfare payment formulae. Second, the institutional changes from AFDC to TANF were built around the ambition to decrease reliance on government support and increase reliance on earned income. This is reflected in the visible decline in welfare participation between 1996 and 1997; the period in which the prescriptions of PRWORA were adopted by States.

As we move up the income distribution, how does the role played by labor supply and income supports change? To examine this, I compute several statistics of interest over three brackets for total annual income. I examine individuals in the sample from three separate brackets: defined by the 33rd and 66th percentile of total annual income in each year. Figure 2.4 shows the mean labor force participation and weekly work hours each income bracket. Although there is little difference

Figure 2.3: Trends in the rate of Welfare Program Participation and Welfare Receipt of CDS Mothers



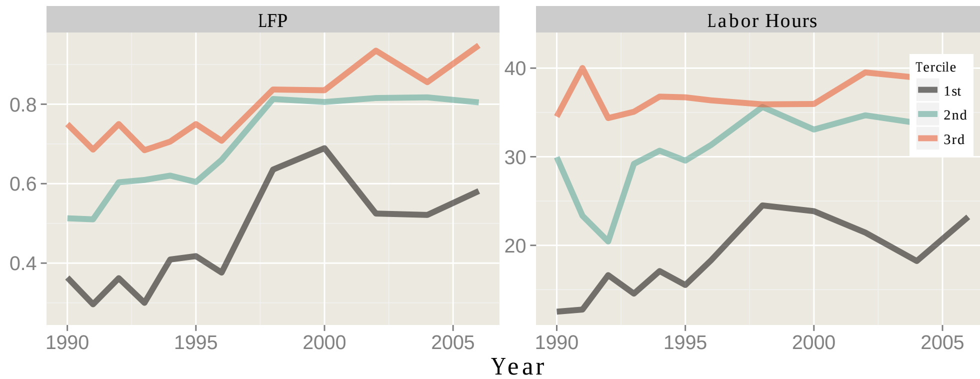
Note: This figure shows the rate of participation in SNAP (left) and AFDC/TANF (right) among CDS mothers in the sample.

in the labor supply behavior of the upper two brackets, we can observe that mothers in the lowest tercile work less on both the extensive and intensive margins than their higher-income counterparts. The large jump in the participation rate of these women mirrors our previous observations on the effect of welfare reform during this time.

Next, I look for cross-sectional and temporal patterns in how households rely on federal income supports to supplement their budget. Figure 2.5 shows the rate of reported participation in AFDC/TANF, the average annual receipt of payments for participating households, and the predicted level of EITC payment for which each household is eligible. To compute the latter statistic, I use the formula for federal EITC on sample mothers' labor income. Since EITC parameters vary by year and by the number of children in the household, I use this information also. Since this excludes the labor income of any co-filing partner, it may not be a reliable estimate of the actual tax credit received by families. However, it should give a useful indication of the size and relevance of this income tranfer for lower income households.

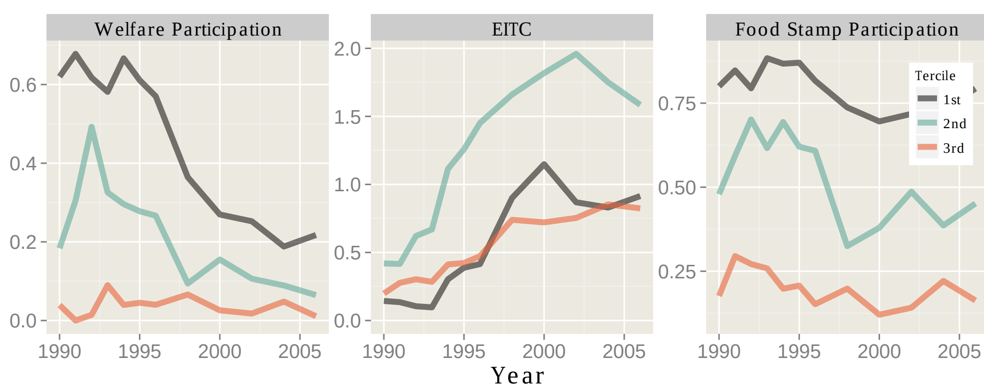
Turning to Figure 2.5, several important features of the data appear. First, all three income deciles rely on welfare support and food stamps to some extent, although the ranking of participation rates corresponds to their ranking in the income distribution in the way that we would expect. Second, families in the lowest income decile, who depend most on welfare, experienced the greatest decline in participation during this time. Finally, we see that mothers in the middle tercile have benefited the most from the expansion in the EITC, while families in the lowest and highest income tercile appear to benefit equally. This is of course driven by the fact that the EITC is increasing in labor earnings, which is at least partly related to the fact that poorer mothers face lower wages in the labor market. This observation is crucial, since it shows that the EITC is not a particularly progressive income support. Given the visible trends, the data shows us that there

Figure 2.4: Average Labor Force Participation and Weekly Hours Worked, by Income Tercile



Note: This figure shows mean weekly hours of labor supplied (conditional on labor force participation (left), and rates of labor force participation (right) for CDS mothers in each tercile of the income distribution. The 33rd and 66th percentiles of income are calculated separately by year.

Figure 2.5: Average Welfare Participation, EITC Receipt, and Food Stamp Participation, by Income Tercile



Note: This figure shows rate of AFDC/TANF participation (left), mean receipt of EITC in thousands of dollars per year (middle), and rate of SNAP participation (right) for CDS mothers in each tercile of the income distribution. The 33rd and 66th percentiles of income are calculated separately by year.

has been a reallocation of transfer dollars away from the families in the deepest levels of poverty towards those with higher earnings. This finding echoes the work Moffitt (2015), who finds the same pattern using the Survey of Income and Program Participation. If one goal of antipoverty programs is to allocate resources to the most needy, this figure suggests that the EITC may not satisfy this goal. In section 5, I will introduce a set of program reforms that attempts to address this issue, and formally explores the trade-offs at play.

A Model of Child Development

As discussed in Section 2, the focus of this paper is on female-headed households. The model formulated in this section reflects this by positioning mothers as sole decision-makers in a family unit.

Although the model includes several stylized features, there are some clear advantages to the structure presented here. First, this approach can include an arbitrary number of child attributes at virtually no additional computational cost. This allows for a rich structure of skill formation. Second, the model admits a closed form, which establishes a clean link between potential instruments and identification of the production parameters of the model.

I abstract away from fertility and divorce decisions. In this setting, family structure is irrelevant to the production problem, while fertility is taken as exogenous. This is a direction for future extension. In addition, we abstract away from any concept of child autonomy in the family environment. Finally, to simplify exposition, I develop the case for a mother with one child. In section B, I show how this can be extended to multiple chidlren with relative ease.

Environment, Production and Preferences

Time in the model is discrete and indexed by t at an annual frequency. Let θ_{it} be a N_θ-dimensional vector[5] that describes the behavioral traits and capabilities of a child at time t. A periods after birth, the child reaches maturity. Maturity is defined as the stage beyond which an individual's skills (θ) no longer develop. I let $t = 0$ be the year of birth, such that in period A[6], the production problem terminates. In every period $t = 0, ..., A-1$, mothers choose their consumption (c), leisure (l), labor supply (h), and program participation (p). Importantly, they can also choose to make investments in their child in the form of money (x) and time (τ). Period A signifies the end of the mother's decision problem, and at this point they receive a terminal payoff from final child abilities, which can be written as $V_{A,i}(\theta)$. In each period $t < A$, utility is derived from consumption, leisure, child abilities, and program participation which has cardinal value determined by the function, u_i.

[5]In my empirical application, I set $N_\theta = 4$

[6]I set $A = 17$ in this paper.

Utility at time t is written as $u_i(c_{it}, l_{it}, \theta_{it}, p_{it})$. Finally, future payoffs are discounted exponentially by a factor, β. I assume that mothers make their decisions to maximize this discounted stream of payoffs.

There are two key ingredients that map parental decisions to the outcomes we wish to analyze: (1) resource constraints; and (2) the technology of child skill formation.

The economic substance of the problem is introduced by resource constraints. First, mothers cannot consume and invest beyond their budget constraint, which is in turn determined by the hours of labor, h, she supplies to the market, her non-labor income and her participation in the Government's transfer or welfare program. Second, the sum of mothers' leisure, time investment, and labor supply must equal the number of hours in one period, which we can normalize to 1. Thus, mothers face a trade-off between earned income through the supply of labor and available hours that may be spent in child-relevant activities or private leisure. I let $\mathcal{H}$ indicate the set of hours from which mothers can choose. In the empirical application that follows, I make labor supply a discrete choice with $\mathcal{H} = \{0, 10, 20, 30, 40\}$. Finally, let $p \in \{0, 1, 2\}$ indicate the mother's decision to participate in the Government's transfer programs, the structure of which I formalize below. These choices correspond to no programs (0), food stamps (1) or food stamps as well as welfare (2). In what follows, let S_{it} be a vector that tracks all variables that are relevant for determining the household budget in period t. With this variable, we can write the budget function as $B_{it}(h, p, S_t)$. S_t will contain variables that are relevant to the determination of wages, non-labor income, as well as the parameters that summarize federal transfer policies.

The evolution of each child's skills $\theta_{i,t}$ over time is determined by a production function. I specify that this technology takes the familiar Cobb-Douglas form:

$$\theta_{k,t+1} = \psi_t x^{\delta_{x,k,t}} \tau^{\delta_{\tau,k,t}} \prod_{j=1}^{N_\theta} \theta_{j,t}^{\delta_{\theta,k,j}} \tag{3.1}$$

Here, $\delta_{x,k,t}$ ($\delta_{\tau,k,t}$) is the Cobb-Douglas share of monetary (time) investment in the production of skill k at age t. Similarly, $\delta_{\theta,k,j}$ indicates the share of the current stock of skill j in the production of next period's future stock of skill k. The coefficient ψ_t represents total factor productivity in production, which I assume is determined as:

$$\log(\psi_t) = X\beta_\theta + \eta_t, \tag{3.2}$$

where X are observable measures of the mother's human capital and η_t is a time-varying component that is known to the mother, but unobservable in our data.

This specification introduces particular dynamics to skill production. For example, the returns to monetary investment at time t are not solely determined by the shares $\delta_{x,t}$, but also by how skills in period $t+1$ shape the formation of skills in period $t+2$, and so on.

One should also note the dependance of the development process on t. This is a natural way to specify production, since it is well known that developmental sensitivities change as children age.

Later, I will take a stand on how the age of the child maps to the relevant developmental stage.

Family Budget and The Policy Environment

To implement the solution described above it is necessary to unpack the components of the budget function, $\mathbf{B}(h,p,S_t)$, and specify the members of the state vector, S_t. This amounts to unpacking the family budget into earnings, non-labor income, and the three sources of government transfers in the form of food stamps, welfare, and taxes. We can write

$$\begin{aligned} B_{i,t} =& \underbrace{w_{i,t}h_{i,t}}_{=E_{i,t}} + N_{i,t} \\ & + \mathbf{1}\{p_{i,t} \geq 1\}T^F(E_{i,t}, N_{i,t}; \mathcal{P}^F_{it}) \\ & + \mathbf{1}\{p_{i,t} = 2\}T^A(E_{i,t}, N_{i,t}, L_{i,t}; \mathcal{P}^A_{it}) + T^T(E_{i,t}, N_{i,t}; \mathcal{P}^T_{it}) \\ =& \mathbf{B}\Bigg(h_{i,t}, p_{i,t}, w_t, N_{i,t}, L_{i,t}, \underbrace{\mathcal{P}^F_{it}, \mathcal{P}^A_{it}, \mathcal{P}^T_{it}}_{\mathcal{P}_{it}}\Bigg) \end{aligned}$$

In this expression, $E_{i,t} = w_{i,t}h_{i,t}$ is earned income from labor hours supplied to the market, $N_{i,t}$ is non-labor income, and (T^F, T^A, T^T) are functions that map these variables to food stamp receipt, welfare receipt, and net taxes. Each transfer is indexed by the set of policy parameters $(\mathcal{P}^F_{it}, \mathcal{P}^A_{it}, \mathcal{P}^T_{it})$, which are mapped to each mother according to the relevant calendar year and her reported state of residence. Furthermore, the functions T^F and T^A incorporate conditions defining the eligiblity of each mother given her sources of income $(E_{i,t}, N_{i,t})$ and accumulated periods of welfare use $(L_{i,t})$. The latter variable applies only after the introduction of time limits for welfare participation.

Members of $(\mathcal{P}^A_{it}, \mathcal{P}^F_{it})$ include the parameters that define gross and net income tests for eligibility, as well as gross and net income for payment calculations. Members of $\mathcal{P}^T_{it}$ include the marginal income tax rates at different income brackets, standard deductions for single-headed households, and the parameters defining federal and state EITC payments.

Further details on the computation of these tax functions and the exact members of each policy vector can be found in Appendix C.

The Family Production Problem

Having described the environment and family preferences, we can move on to stating the dynamic programming problem faced by the family unit. I proceed by stating the problem, then describing the relevant notation. Recall that the terminal period of the problem occurs at A, the time period at which the child matures. I state below the problem for every time period $t < A$:

$$V_t(\theta_t, S_t, \eta_t) = \max_{c,l,x,\tau,h\in\mathcal{H},p} \Big\{ u(c,l,\theta_t,p) + \beta\mathbb{E}[V_{t+1}(\theta_{t+1}, S_{t+1}, \eta_{t+1})\ |S_t] \Big\} \tag{3.3}$$

Subject to the constraints:

$$c + x \leq \mathbf{B}(h, p, S_t) \tag{3.4}$$

$$l + \tau + h = 1 \tag{3.5}$$

$$\theta_{k,t+1} = \psi_t x^{\delta_{x,k,t}} \tau^{\delta_{\tau,k,t}} \prod_{j=1}^{4} \theta_{j,t}^{\delta_{\theta,k,j}}, \text{ for } k = 1, 2, .., N_\theta \tag{3.6}$$

In this setup, equation (3.4) is the budget constraint. The function $\mathbf{B}$ defines the budget set for the family as a function of parental labor supply, h, program participation, p, and relevant economic state variables, S_t. In this setup, S_t is permitted to evolve dynamically with parental decision making. Most importantly, S_t includes all variables that summarize the policy environment faced by mothers, including the welfare and tax policy applicable at time t. One particularly important dynamic component of the decision making problem will involve the introduction of time limits, which I detailed in section 3.2. Finally, (3.5) describes the time constraint faced by the mother.

To close the model, we specify the form of utility, u, and the terminal value function:

$$u(c, \tau, \theta, p) = \alpha_c \log(c) + \alpha_l \log(l) + \alpha_\theta \cdot \log(\theta) + \alpha_F \mathbf{1}\{p = 1\} + \alpha_A \mathbf{1}\{p = 2\} \tag{3.7}$$

$$V_A(\theta) = (1 - \beta)^{-1} \alpha_\theta \log(\theta) \tag{3.8}$$

Finally, for notational convenience, we can write the production function in the following vector notation:

$$\log(\theta_{t+1}) = \delta_{x,t} \log(x) + \delta_{\tau,t} \log(\tau) + \delta_{\theta,t} \log(\theta_t) + \eta_t \tag{3.9}$$

For reasons made clear in Appendix B, this assumption is pivotal in reducing the computational complexity of the problem. Since θ is a vector, $\delta_{x,t}$ and $\delta_{\tau,t}$ are N_θ dimensional vectors of Cobb-Douglas shares. Assuming log utility, as in (3.7), facilitates the derivation of closed-form expressions for investment policies. This is also demonstrated in the model solution found in Appendix B. Finally, I specify that the terminal value V_A is equal to the discounted present value of utility derived from each child's final abilities over an infinite horizon [7].

Assumptions (3.7) and (3.6) lead to the following simplification of the dynamic program. In Appendix B, I formally derive the following expressions in the general case that allows for multiple children. Let me relegate technical details to that section, presenting here the substantive model implications and some informal discussion. The value function can be written as additively separable in the skill vector θ:

$$V_t(\theta, s_t, \eta_t) = \alpha_{V,t} \log(\theta_t) + \alpha_{V,t+1} \log(\eta_t) + \nu(S_t) \tag{3.10}$$

$$\nu(s_t) = \max_{h \in \mathcal{H}, p} \left\{ \overline{\alpha}_{c,t} \log(\mathbf{B}(h, p, S_t)) + \overline{\alpha}_{l,t} \log(1 - h) + \beta \mathbb{E}[\nu(S_{t+1}) \mid S_t] \right\} \tag{3.11}$$

[7] This specification can be easily made to correspond exactly to the right value for a fully-specified infinite horizon problem.

In this formulation, the parameters $\overline{\alpha}_{c,t}$ and $\overline{\alpha}_{l,t}$ are aggregates that represent the total value of income and leisure, respectively. They can be written as:

$$\overline{\alpha}_{c,t} = \alpha_c + \beta\alpha_{V,t+1}\delta_{x,t} \tag{3.12}$$

$$\overline{\alpha}_{l,t} = \alpha_l + \beta\alpha_{V,t+1}\delta_{\tau,t} \tag{3.13}$$

We see that the utility derived from income is composed of two terms: α_c is of course the value derived from private consumption, while $\beta\alpha_{V,t+1}\delta_{x,t}$ is the marginal return of investment to each skill, scaled by the value derived from each skill next period, $\alpha_{V,t+1}$, and discounted by β. The value derived from skills in each period, $\alpha_{V,t}$ can itself be expressed recursively:

$$\alpha_{V,t} = \alpha_\theta + \beta\alpha_{V,t+1}\delta_{\theta,t}. \tag{3.14}$$

The value from skills is the sum of utility derived from each skill today (α_θ) and the return of each skill to the production of future skills, scaled by the value of these in the next period ($\beta\alpha_{V,t+1}\delta_{\theta,t}$). Since terminal utility V_A also takes this log-linear form, we can see how this recursion holds in each period. Finally, preservation of the log-additivity of the value function leads to the following proportional investment rules:

$$x_t = \underbrace{\frac{\beta\alpha_{\theta,t+1}\delta_{x,t}}{\overline{\alpha}_{c,t}}}_{=\phi_{x,t}} \mathbf{B}(h, p, S_t) \tag{3.15}$$

$$\tau_t = \underbrace{\frac{\beta\alpha_{\theta,t+1}\delta_{\tau,t}}{\overline{\alpha}_{l,t}}}_{=\phi_{\tau,t}}(1-h) \tag{3.16}$$

This formulation of the problem greatly simplifies computation, since the value function in terms of the skill vector θ can be solved in closed form. The key to this result is that, subject to a log transformation, the current realization of θ does not effect the productivity of investments. Thus, the value of current θ can be expressed as a linear combination of period utility and the discounted return to future skills, as defined by the share of θ in production, $\delta_{\theta,t}$. This is formalized in expression (3.14). Since we have log-utility, these coefficients describe in (3.15) the relative share of income spent on the child and in (3.16) the relative share of non-labor hours spent in time investment. The proportional investment rules, when substituted into the dynamic program, allow us to simplify the problem to one of labor supply and program participation, as shown in (3.10) and (3.11). The coefficients $(\overline{\alpha}_{c,t}, \overline{\alpha}_{\tau,t})$ define the labor supply problem, and adjust each period to reflect the relative importance of time and money in the production of child skills.

Estimation

Heterogeneity and Preferences

The model admits a normalization in the scale of utility. Thus, I set $\alpha_c = 1$. In addition, I let mothers value their leisure α_l in the same way, while allowing the extent to which they privilege their child's outcomes (α_θ) to vary in the population.

In this setup, I allow preferences over child outcomes to be heterogeneous. Although α_θ is an N_θ-dimensional vector, I let the heterogeneity across mothers be defined by a scalar, ζ, that scales parental utility derived from θ.

$$\alpha_{\theta,i} = \zeta_i \overline{\alpha}_\theta, \ \zeta \sim G_\zeta \tag{4.1}$$

Indexing preference heterogeneity by a scalar greatly reduces the complexity of the estimation problem, however it also provides a convenient simplification of the identification problem, which I discuss in the following section.

Identification

The results of later policy experiments hinge crucially on the importance of time and money investments on child outcomes (summarised by parameters δ_x and δ_τ) and on the dynamic complementarities of skill production (embodied in δ_θ). In this section I briefly discuss how these parameters can be identified without leaning too heavily on the structure or assumptions of the behavioral model.

To see this, begin by taking the outcome equation (3.6) and substituting in the investment policies (3.15) and (3.16). Let B_t indicate total family income in period t. We obtain the expression:

$$\log(\theta_{k,t+1}) = \delta_{x,a_k} \log(B_t) + \delta_{\tau,a_k} \log(1 - h_t) + \delta_{\theta,a_k} \log(\theta_{k,t}) + \varepsilon_{k,t} + \eta_{k,t} \tag{4.2}$$

$$\varepsilon_{k,t} = \delta_{x,a_k} \log(\phi_{x,t}) + \delta_{\tau,a_k} \log(\phi_{\tau,t}) \tag{4.3}$$

This expression relates child outcomes to two important observables: total income, B_t, and total available hours $1 - h_t$. In addition, the expression incorporates unobservables $\varepsilon_{k,t}$ and $\eta_{k,t}$. While the inclusion of $\eta_{k,t}$ is innocuous in this setup, $\varepsilon_{k,t}$ warrants further comment. First, note that it serves as a "fixed effect" in the sense that the error term is a function of the investment shares $(\phi_{c,t}, \phi_{\tau,t})$ which are themselves functions of time-invariant preferences. However, this mapping is time-varying due to the dynamic structure of skill production. Second, equation (4.3) shows that the ith component of $\varepsilon_{k,t}$ is the sum of the Cobb-Douglas share of each investment type for skill i, multiplied by the fraction of either dollars or hours that is dedicated to this investment type. Thus, parents that have a greater preference weight on child outcomes will have higher realizations of $\varepsilon_{k,t}$ and hence will appear more productive in this specification. This presents an identification problem because $\varepsilon_{k,t}$, if indeed unobservable, is correlated with realizations of income and labor supply. There are two reasons for this. First, all three variables are a function of maternal preferences. Second, these preferences may also be correlated with state variables S_t that govern the budget constraint and hence both endogenous variables.

In this paper I propose two methods of identification. First, let the state S_t be decomposed into $[Z_t, W_t]$ where Z_t represents variables that are exogenous to ζ, which indexes preference heterogeneity in this model. We can identify production parameters using the moment condition:

$$\mathbb{E}[\log(\theta_{k,t+1}) - \delta_{x,a_k}\log(B_t) - \delta_{\tau,a_k}\log(1-h_t) - \delta_{\theta,a_k}\log(\theta_{k,t}) \mid Z_t] = 0. \tag{4.4}$$

Since there are two important and exogenous policy changes that transpire during the relevant sample period, these propose a natural set of instruments from which to identify parameters.

In addition to this strategy, I exploit the availability of unique data on time investment from the CDS sample. In the model solution, equation (B.13) shows that the share of available time devoted to time investment, $\phi_{\tau,t}$ is a function of preferences, α_θ, and the ages of each child in the family, $\mathbf{a} = \{a_k\}_{k\leq N_K}$. In addition, my assumption that heterogeneity in preferences is indexed by a scalar variable, ζ, implies that there is a monotonic one-to-one mapping between ζ and $\phi_{\tau,t}$ for any given $\mathbf{a}_t$. From the time diary supplement, we can use the time investment aggregate, τ_{97}, to construct a measurement of $\phi_{\tau,97}$:

$$\phi_{\tau,97} = \frac{\tau_{97}}{1-h_{97}} \tag{4.5}$$

By the argument above, since the mapping from ζ to $\phi_{\tau,97}$ is monotonic, we can invert this function to give:

$$\zeta = \Phi^{-1}(\phi_{\tau,97}, \mathbf{a}). \tag{4.6}$$

This permits the derivation of the following condition:

$$\mathbb{E}[\varepsilon_{k,t} \mid h_t, B_t, \phi_{\tau,97}, \mathbf{a}] = \mathbb{E}[\varepsilon_{k,t} \mid \phi_{\tau,97}, \mathbf{a}] = \varphi(\phi_{\tau,97}, \mathbf{a}) \tag{4.7}$$

Thus, the addition of a nonparametric control function in the specification (4.2) allows us to add the typical orthogonality restrictions of non-linear regression to the moment restrictions given by the instruments:

$$\mathbb{E}[\log(\theta_{k,t+1}) - \delta_{x,a_k}\log(B_t) - \delta_{\tau,a_k}\log(1-h_t) - \delta_{\theta,a_k}\log(\theta_{k,t}) \; - \varphi(\phi_{\tau,97}, \mathbf{a}) \mid h_t, B_t] = 0 \tag{4.8}$$

In combination, these moment conditions allow us to identify the production parameters of the model, $(\delta_x, \delta_\tau, \delta_\theta)$, without using assumptions regarding the co-dependance of unobservables on the choice variables, (B_t, h_t).

Estimation Method

I estimate the model using minimum distance on a collection of statistics from the data. Most importantly, I include the vector of covariances that collectively define the Instrumental Variable and Control Function estimates implied by equations (4.4) and (4.8). I use applicable EITC and welfare parameters in each year, as well as state-level unemployment rates as potential instruments. I use a 2nd order polynomial in the empirical measure of $\phi_{\tau,97}$ described in the previous section. In addition to these statistics, I match a series of interactions between explanatory variables with wage and non-labor income. I also match labor supply, welfare receipt and participation in the pre and post-reform eras. In total, I compute 152 moments from the data. Table A.6 shows a subset of these moments. Let Γ be the full vector of moments and statistics computed from the data. In addition to the parametric assumptions described above, to simulate the model I assume that $\epsilon_{TW}, \epsilon_w, \epsilon_N$ are normally distributed with mean zero and standard deviations $(\sigma_{TW}, \sigma_w, \sigma_N)$. I additionally assume that ζ is log-normally distributed with mean $\mu_{\alpha,\theta}$ and standard deviation $\sigma_{\alpha,\theta}$. Let ω signify the full vector of parameters of the model, and let $\Gamma(\omega)$ be the vector of simulated moments that corresponds to Γ. The classical minimum distance estimator, $\hat{\omega}_{MD}$ is produced as:

$$\hat{\omega}_{MD} = \arg\min_{\omega} (\Gamma(\omega) - \Gamma)' \mathbf{W} (\Gamma(\omega) - \Gamma). \tag{4.9}$$

I choose the weighting matrix $\mathbf{W}$ to have zeros in the off-diagonal entries, and $1/\mathbb{V}(\Gamma_i)$ in the diagonal entry at position (i, i), where $\mathbb{V}(\Gamma_i)$ is the variance of the ith statistic, calculated by bootstrap resampling.

Results

Table A.2 presents the results for the baseline model. In this specification, we allow non-labor income and wages to vary according to: mother's education (ED_i), the mother's score on a passage comprehension test (PC_i) and a self esteem scale (SE_i) administered in the PCG survey, mother's age (age_{it}), the state level unemployment rate (unemp_{it}), and the year (Y_{it}). The results indicate that each variable is important in explaining some portion of the variation of wages and non-labor income. I estimate the standard deviation in preferences over child skills ($\log(\alpha_\theta)$) to be 0.5625 which suggests that some of the variation in child outcomes is driven by how mothers invest in their children, even when conditioning on financial and temporal resources. We explore this proposition later in this section. In addition, I estimate significant variation in the determination of wages and non-labor income (σ_w, σ_N).

In the baseline, production parameters are specified to vary with age according to:

$$\delta_{S,J,z,a} = \exp(\gamma_{SJ,z,0} + \gamma_{S,J,z,a} \times a) \text{ for } S, J \in \{LW, AP, BE, BN\}, \text{ for } z \in \{x, \tau\} \tag{4.10}$$

By contrast, estimates of δ_θ are not permitted to vary by age, but are permitted to take negative values. Table A.3 presents the estimates of these parameters, in addition to the contribution of mother's education and passage comprehension to skill production.

However recall that the production technology, when taken in logs, adopts a VAR structure. Thus, there are significant dynamic interactions over time that make these parameter estimates difficult to interpret. For example, the marginal response of skills in period $t+s$ to monetary investment in period t can be expressed as:

$$\frac{\partial \log(\theta_{t+s})}{\partial \log(x_t)} = \left(\prod_{j=1}^{s-1} \delta_{\theta,t+j}\right) \delta_{x,t} = \delta_\theta^{s-1}\delta_{x,t}, \tag{4.11}$$

where the second equality above follows under the simplifying assumption that $\delta_{\theta,t} = \delta_{\theta,s}$ for all t, s. Thus, to interpret first the overall importance of each investment type, I calculate the total contribution of each investment type to final skills. This is facilitated by the representation of final period skills as:

$$\log(\theta_{T_M}) = \sum_{t=0}^{T_M-1} \delta_\theta^{T_M-t-1}(\delta_{x,t}\log(x_t) + \delta_{\tau,t}\log(\tau_t) + X\beta_\theta) \tag{4.12}$$

Thus, in Table A.4 I report the following set of coefficients:

$$\sum_{t=0}^{T_M-1} \delta_\theta^{T_M-t-1}\delta_{x,t}, \qquad \sum_{t=0}^{T_M-1} \delta_\theta^{T_M-t-1}\delta_{\tau,t}, \qquad \sum_{t=0}^{T_M-1} \delta_\theta^{T_M-t-1}\beta_\theta \tag{4.13}$$

The first two columns of the table show the overall contribution of mother's education and passage comprehension score to final skill outcomes. Signs are mixed in this case, indicating that there may not be strong patterns between maternal human capital and child outcomes in this sample. The third and fourth columns show the contribution of money and time investments to final skills. Each coefficient in these columns can be interpreted as the percentage change in skills (scaled by its association with high-school graduation) in response to a 1% increase in each investment type. For example, a 1% increase in monetary investment in every period leads to a decrease in externalizing behaviors that is associated with a 10% point increase in the rate of high school graduation. This magnitude of elasticity is striking, however it is important to remember two caveats. First, although my empirical strategy argues for a causal interpretation of the relationship between investment and skills, the anchoring relationship between skills and graduation is not. Second, the elasticities presented here cannot be interpreted as policy parameters. To use the above example, a lump-sump transfer of income, aimed at increasing each household's budget by 1%, would cause a reduction in labor supply, offsetting the intended effect of the transfer and causing a substitution away from monetary investment into time investment. In the case of externalizing behaviors, Table A.4 indicates that time investment is less productive and thus, a transfer of this kind cannot replicate the numbers drawn from our interpretation of the production parameters.

Table A.4 demonstrates that both investment types have a significant role to play in the formation of child skills. In particular it appears that in aggregate, time is more influential in shaping cognitive outcomes, while money is more influential when it comes to behavioral problems. To get a more precise picture of how investment shares vary with age, I plot the contribution of time and money investments to final skills in Figure 4.1. Recall that, according to expression (4.12), the contribution of monetary and time investments in time t to final skills can be expressed as:

$$\delta_\theta^{T_M-t-1}\delta_{x,t}, \qquad \delta_\theta^{T_M-t-1}\delta_{\tau,t}$$

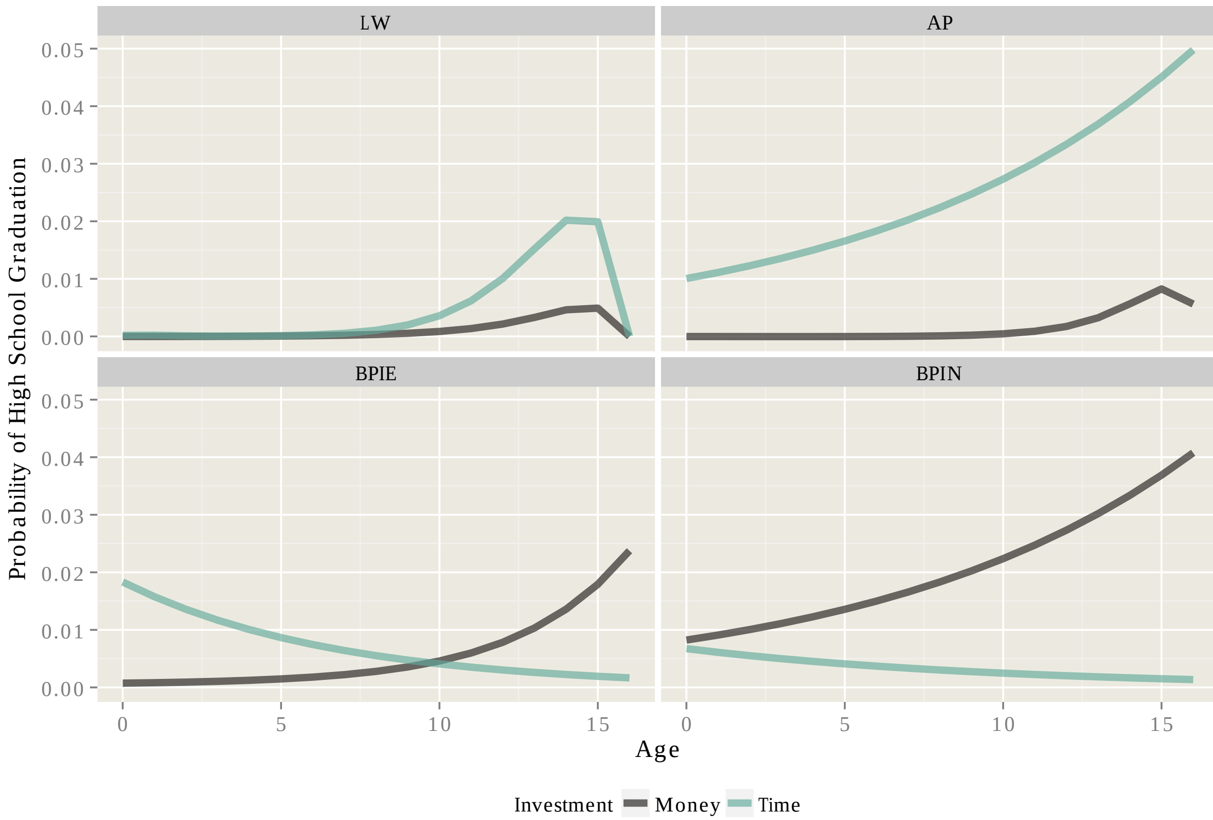


Figure 4.1: Contribution of time and money investment to final skills, by age

Figure 4.1 shows interesting dynamic patterns in the importance of different investments by age. In the production of behavioral traits, time is initially more influential, but cedes importance to monetary investments later in the development process. Contrastingly, contributions of either investment to the production of cognitive skills do not become significant until late childhood or early adolescence.

The estimates of production parameters imply that time and money investments both play a crucial role in the formation of cognitive and behavioral traits. This should serve as confirmation that differently designed labor market and income transfer policies have the potential to produce markedly different human capital outcomes. As a final inspection of the estimates, I once again exploit the fact that expression (4.2) can be iterated forward such that final skill outcomes can be written as

$$\log(\theta_{i,17}) = \Gamma_x \log(\mathbf{B}_i) + \Gamma_\tau \log(1 - \mathbf{h}_i) + \overline{\varepsilon}_i + \overline{\eta}_i \tag{4.14}$$

Where $\mathbf{B}_i$ and $\mathbf{h}_i$ are vectors containing family income and mother's labor supply in every year of childhood for child i, the error term $\overline{\varepsilon}$ is a weighted sum of the marginal propensities to invest at each age ($\log(\phi_{i,x,t}), \log(\phi_{i,\tau,t})$, as in (4.3)), and the error term $\overline{\eta}$ is a weighted sum of the development shocks $\eta_{i,t}$. This expression allows us to think about the contribution of variation in preferences (through ε) and development shocks (through η) to skill inequality. In particular, by calculating the variance of the terms $(\bar{\varepsilon}, \bar{\eta})$ we can calculate a lower bound on the contribution of preferences and shocks to the overall variance in skills. I present these calculations in Table A.5, which shows that in combination these variables explain a large portion of variance in final skills. One observation of note is that we see that variation in the marginal propensity to invest (through heterogeneous preferences) explains a large portion of the variance in cognitive skills. In addition, we see that a relatively small role is left to be played by variation in economic circumstances (as reflected by $\mathbf{B}$ and $\mathbf{h}$) in overall skill inequality. Alternatively, we can make the interpretation that, even if economic inequality were to be removed by equalizing economic resources, we would still see significant residual inequality, driven both by random shocks and by differences in the rate at which these resources are translated into investments.

While this exercise in variance decomposition is useful for thinking about the role played by economic resources in shaping inequality, it is crucial to note that it does not provide insight into the potential gains in bolstering resources for poor families. Furthermore, while our analysis of production parameters here reveals an important role to be played by money and time investments, it does not provide a complete picture of how to leverage policies to improve child outcomes. In the next section, I consider the potential effect of several policy initiatives that attempt to improve income support for poor families.

Policy Analysis

In the previous section we confirmed that the model provides a reasonable fit of the data and produces production parameter estimates that leave ample room for transfer policies to influence development outcomes. In this section, I draw out specific policy implications from the estimated model. These are shaped in particular by two important features of the model: the contribution of time and money to children's human capital outcomes, and the response of parents to changes in the structure of the policy environment. We will find that parental responses to program incentives demonstrate significant heterogeneity, which has major implications for the distributional impacts of policy reforms.

As discussed in Section , the sample period saw highly relevant changes to the shape of antipoverty programs in the US. In particular, the shift in funding away from unconditional transfer programs such as TANF and towards work supplements such as the EITC has effectively generated a redistribution of assistance away from families at the deepest levels of poverty (Moffitt, 2015).

Motivated by this observation, this section is dedicated to understanding both the aggregate and distributional impacts of particular welfare design choices. This will be achieved by virtue of two counterfactual simulations that vary in their use of unconditional transfers and work supplements. First, I consider the introduction of a Basic Income Standard (BIS), which effectively remediates the observed shift of government resources away from the neediest mothers in the sample, and alleviates the deepest levels of poverty observed in our sample. Second, I consider a policy reform that combines a BIS with earnings supplements, similar to the EITC. While the first policy

In particular, I will look at policy changes that are *cost neutral*, where any change in program costs includes both the value of transfers, as well as the level of tax receipts. An alternative to this type of analysis would be to consider expansions in the current size of the welfare program, and weight the long-term economic benefits of such expansions against their costs. However, an adequately rich version of this analysis requires access to a wide-ranging and lengthy panel of adult outcomes, with which to properly measure the long-term effect of policy changes. While the PSID may provide such an opportunity in the future, the current span of data on children of the CDS is too limited for such a purpose.

However, in order to give an interpretable scale to counterfactual skill outcomes, and evaluate the long-term impact of policies, I exploit the availability of socioeconomic outcomes in young adulthood for children of the CDS. In particular, using data on high school graduation, I estimate a linear probability model:

$$HSG_i = \mathbf{1}\{\theta_i \beta_{HSG} - U_i \geq 0\},\ U \sim \text{unif}[0, 1] \tag{5.1}$$

I use the estimates of this model to simulate high school graduation rates from the counterfactual distribution of skills generated by the policy experiments. Estimates for this model are presented in Table A.1. In the discussion that follows, I suppose that this outcome equation is valid, and therefore discuss counterfactual graduation rates with causal language. However, one can alternatively suppose that this equation is simply a means by which we can weight aggregate skill outcomes: by their respective association with high school graduation in a jointly estimated model.

In the remainder of this section, I will describe the specific quantitative properties of the two reforms, and provide an analysis of their aggregate and distributional impacts.

Two Policy Reforms

In the first counterfactual, I guarantee \$6,500 a year to each household with a child under the age of 17. This transfer is reduced at a rate of 50% as mothers receive any income from other sources. Note that, conditional on cost-neutrality, there is a trade-off between the size of the unconditional transfer (as determined by the basic income standard) and the effective marginal tax rate on earnings (as determined by the phase-out rate). Increasing the income standard and reducing the phase-out rate both increase the cost of the program, the former by increasing the size of the transfer, conditional on receipt, and the latter by broadening the base population of eligible families.

In the second counterfactual, I combine a minimum income standard with a work incentive, which takes the traditional shape of the earned income tax credit schedule. The total payment, $\mathcal{T}^*$ to a family can be summarised by the following formula:

Figure 5.1: Transfer schedules in \$/month for two proposed counterfactual programs.

This figure shows the value of the transfer program $\mathcal{T}^*(E, N)$ described in equation (5.2), setting $N = 0$. Values are converted from annual numbers to dollars per month. The program "Minimum Income" is a Basic Income Standard of \$6,500 a year with a 50% phase-out. The "Optimal Reform" takes the values described in the text.

$$\mathcal{T}^*(E, N) = \max\{\pi_{\text{BIS}} + \min\{R_{\text{in}}E, \pi_{\text{cred}}\} - R_{\text{out}} \max\{E + N - I_{\text{out}}, 0\}, 0\}, \tag{5.2}$$

where E is household earnings and N is any income from non-labor sources. Here, π_{BIS} serves as the basic income standard, while $R_{\text{in}}, R_{\text{out}}$ are the rates at which the credit is phased in and out, π_{cred} is the maximum earnings credit, and I_{out} is the income threshold at which the transfer begins phase-out. In this context, the first policy reform can be thought of as one in which the parameter set $(\pi_{\text{BIS}}, \pi_{\text{cred}}, R_{\text{in}}, R_{\text{out}}, I_{\text{out}})$ is equal to $(6500,\ 0,\ 0,\ 0.5, 0)$.

To set the parameters of this new program, a search over combinations of the parameters $(\pi_{\text{BIS}}, \pi_{\text{cred}}, R_{\text{in}}, R_{\text{out}}, I_{\text{out}})$ to maximize the counterfactual rate of high school graduation, subject to the constraint of cost-neutrality. This routine produces a transfer program with the following parameters:

$$\pi_{\text{BIS}} = 1200,\ \pi_{\text{cred}} = 3300,\ R_{\text{in}} = 0.5,\ R_{\text{out}} = 0.33,\ I_{\text{out}} = 10000.$$

This produces a starkly different program to the BIS that was proposed for the first counterfactual, as shown in Figure 5.1. In particular, the optimal program leans much more heavily on work incentives than the baseline proposal, which does not use them at all. In the next section, I will discuss the aggregate impacts of these programs and discuss the trade-off between using unconditional transfers and using earnings supplements.

Results and Analysis

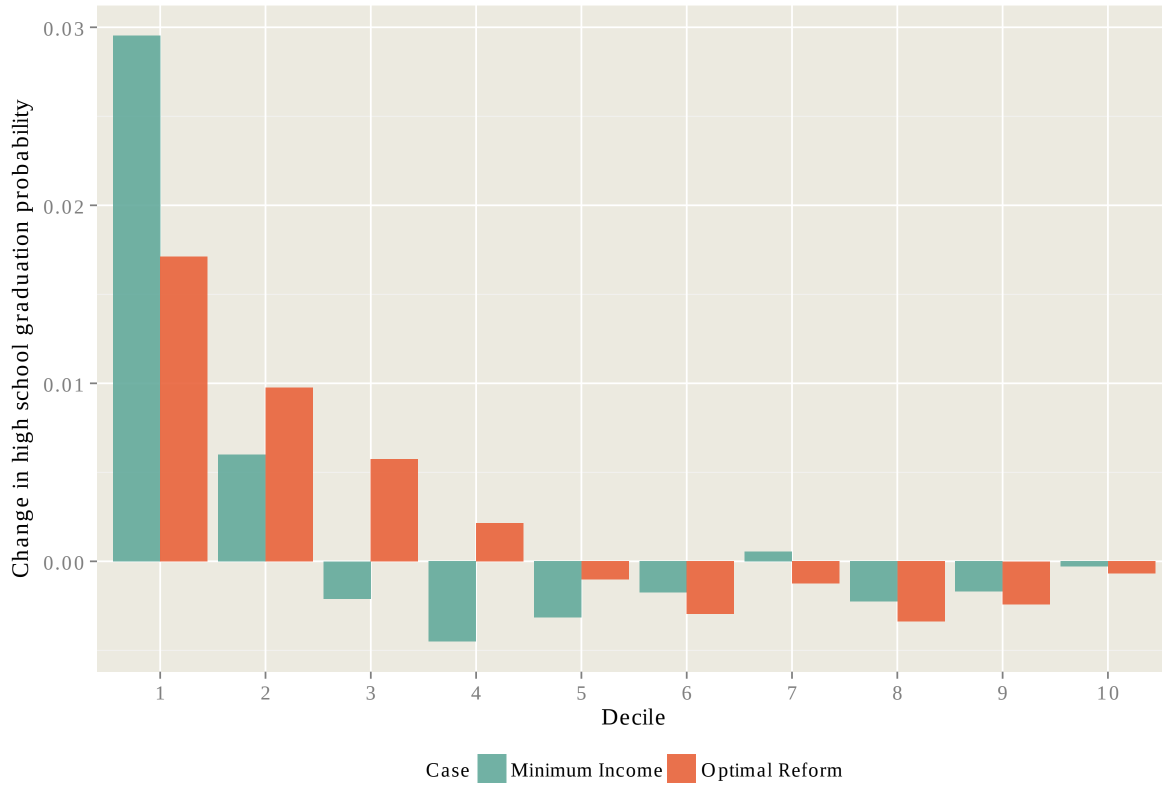
Aggregate Impacts

To assess the relative impact of these reforms, I re-simulate outcomes from the model under each counterfactual program, for the same panel windows that apply to mothers in the PSID data. In Table A.8 I report the average weekly hours supplied to the market and average annual income across families in thousands of dollars. In addition, I report the change in the average rate of high school graduation, and the average change in maternal welfare, as measured by consumption equivalent variation. This measure is computed using the value to each mother at the beginning of their dynamic program. Thus, for example, the average change in welfare when moving to the optimal reform is the equivalent of increasing the consumption of each mother in every period by 0.32%.

We can see that both programs lead to aggregate increases in welfare and skill outcomes. Why does the optimal program have a smaller basic income and a larger work incentive? It will be useful to informally discuss this policy trade-off as it sheds light on future distributional concerns. First, note that an earnings supplements and a direct transfers of equivalent cost will have very different impacts on total income and hours. For example, \$1 in lump sum transfer will cause a reduction in labor supply and an increase in hours at home, resulting in an income change of less than \$1. By contrast, \$1 spent on earnings supplements causes an increase in labor supply (a decrease in hours at home) and an income change of more than \$1. In this sense, earnings supplements are a cheaper means of increasing income, but this is achieved at a cost in terms of hours at home. It follows, then, that the overall impact on child outcomes crucially depends on estimates of δ_x and δ_τ. For example, if $\delta_\tau = 0$, implying no role for time in the development process, the government would strongly prefer to use labor supply incentives over direct transfers.

While the magnitudes of improvements in maternal welfare and the rate of high school graduation seem small, it is important to remember that these gains have been achieved at zero cost, in the sense that the proposed program reforms are cost-neutral. Furthermore, in the next section we will document the fact that these averages obscure large changes in outcomes for specific subgroups in the sample.

Figure 5.2: Impacts on high school graduation across income deciles of (1) Basic income standard; (2) Basic income with earnings tax credits



Note: This figure shows the predicted change in the rate of high school graduation for the two policy reforms, for children in each income decile at baseline. Reformed transfer policies are shown in Figure 5.1.

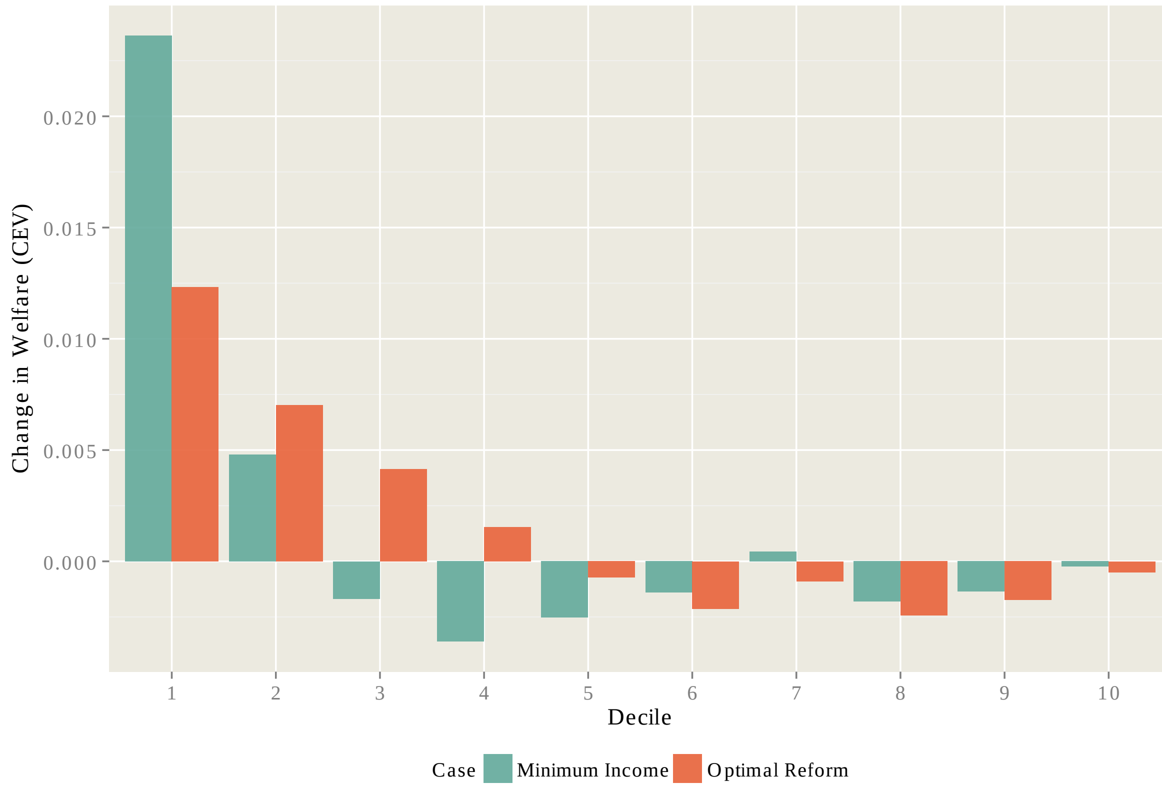
Distributional Impacts and Policy Trade-Offs

While the preceding section demonstrated that there are potential efficiency gains to using work incentives in transfer programs, there are reasons to be interested in more than just the aggregate impact of particular design choices. Mothers benefit from and respond differently to differently shaped programs due to heterogeneity in their preferences and economic circumstances. Thus, we should expect the response to different reforms to exhibit significant variation across the population.

To assess these distributional concerns, I next examine program impacts by deciles of the income distribution at baseline. Specifically, I first divide families into 10 bins, based on their mean annual income across the length of their respective panels. Next, I calculate the mean change in the rate of high school graduation (our chosen skill aggregate) to assess the impacts of policy reforms across the distribution.

Figure 5.2 shows the results of this exercise, which unveils a large degree of heterogeneity in program impacts across the population. There are, in particular, two important insights to be

Figure 5.3: Consumption equivalent variation from change to (1) Basic income standard; (2) Basic income with earnings tax credits



Note: This figure shows the predicted change in maternal welfare (as measured by consumption equivalent variation) for the two policy reforms, for children in each income decile at baseline. Reformed transfer policies are shown in Figure 5.1

gained by examining reform effects across the distribution. First, we see that children in the lowest decile enjoy the largest skill gains from both reforms. For example, the introduction of the BIS induces a nearly 3% increase in the rate of high school graduation for these children. The optimal program delivers less benefits, however, with an increase of about 1.7%. This comparison invites the second insight: that these two programs, while both advantageous, distribute gains differently across the distribution. The optimal program, by utilizing earnings supplements, allocates comparatively more resources to mothers with higher wages and a greater preference for work. In this sense, it is less progressive, since it transfers less to the most economically deprived children. Figure 5.3 demonstrates that these patterns are replicated when considering the welfare changes (as measured by consumption equivalent variation) to mothers in the simulation. While maternal welfare is not the outcome of focus in this study, it is an important robustness check to verify that improvements in skill outcomes are not accompanied by dramatic losses in maternal welfare, since this would introduce another important policy trade-off that lies outside the scope of this exercise.

This important difference in distributional impacts reveals an *equity-efficiency trade-off*. There is fundamental tension between the efficiency gains from using work incentives (in this case, in the form of earnings supplements) and the fact that these transfers do not benefit children facing the greatest economic disadvantage: those with mothers earning low wages and possessing a greater preference for leisure. The implications of this result are clear: a prospective social planner must set their preferences over distributional outcomes in order to decide on a preferred policy. Furthermore, within the space of policies considered in this paper, such preferences will quite significantly determine the shape of an "optimal" program.

The presence of this trade-off also has implications for the evaluation of previous reform impacts. In particular, it implies that while some mothers and children have potentially benefited from the historical shift in the US away from traditional welfare and towards earnings supplements, others have likely been made worse off. In recent work, Moffitt (2015) expresses exactly this concern, showing that government transfers have been redistributed away from families at the deepest levels of poverty and towards families with higher levels of baseline earnings. My analysis confirms this insight, and validates the concern that such a change might be particularly harmful for societies' most disadvantaged children.

Conclusion

In this paper I investigated how household economic resources and government transfer policies influence child outcomes. To do this, I developed a dynamic, empirical model of maternal labor supply and investment in children. A key advantage of this approach is that the parental response to a rich portfolio of welfare and labor market policies is fully articulated. I combine this structure with a transparent approach to identification of the technology of skill formation. I find that both household income and time investment play an important causal role in shaping the behavioral and cognitive traits of children: increasing either investment good by 1% can, in select years, boost final cognitive and behavioral skills by up to 7.5% points, when anchored to the probability of high school graduation.

Next, I used estimates of the model to see how effectively government transfer programs can be used to improve child skill outcomes. I find that attempting to boost child skills through direct income supports is expensive, since it necessitates a persistent increase in resources over every period, and because the returns to additional family income and maternal time quickly diminish. Consequently, programs are most effective when they assist the poorest mothers in the sample, for whom the marginal returns to additional resources are greatest. In this spirit, I design a counterfactual income support based on a minimum income standard that is *cost neutral*. That is, it costs the same in simulation as AFDC/TANF and the EITC combined. Evidence from simulations suggested that such an initiative is highly promising: skills in the bottom decile of the income distribution - families who face extreme economic disadvantages and only partial welfare coverage - are lifted substantially, inducing a 3% point increase in high school graduation rates.

Despite the strength of these results, there are some necessary caveats. My results suggest that mothers are highly responsive to labor supply incentives. As such, the unconditional provision of a minimum income standard has strong negative impacts on labor supply attachment. Since, in this paper, I have not assigned any policy importance to labor supply, I do not see this as a weakness in the program. However, the political substance of the PRWORA reforms was to discourage welfare dependance and encourage labor supply. To this extent, the significant boost in child skills that my proposal induces can be weighed against its impact on maternal labor force attachment.

Furthermore, it is worth noting that the parameters of the minimum income standard can be adjusted to provide stronger labor supply incentives. The tradeoff, as has been established by my work here, is that these programs are not maximally progressive. A revenue neutral shift from unconditional income to earnings supplements shifts transfers away from mothers with the lowest wages and the greatest preference for leisure. For programs of equivalent cost, work incentives are less helpful for the most disadvantaged children. This study has shown that the magnitude of such effects cannot be ignored in any policy discussion on this topic.

Finally, this paper represents an important first step in a broader research program aimed at modelling the developmental role of income supports in poor families. Directions in which to extend this analysis include, but are not limited to: endogenous household formation, endogenous fertility, child care, involuntary unemployment, and including a richer developmental production technology. For example, the technology and preferences assumptions in this model make the number of time use and expenditure categories irrelevant. However, it seems intuitively true that different categories of expenditure and time use play different developmental roles that may vary according to the child's current stock of cognitive and behavioral traits. For example, food expenditure is likely to be an investment category which is essential, up to a level of sustenance, with little productive return beyond sufficiency. An additional example: a child that suffers from behavioral problems may benefit from more remedial time use activities (for example, those that allow for active supervision) compared to a less troubled child, who may benefit more from self-directed study. This extra richness is intricately tied to the economic realities of poverty, in which frequent income shocks may affect parental investment strategies and time use habits. Such shocks may also have long-lasting impacts, which the structure of this model does not allow.

There is sufficient evidence in this work to justify a more detailed look at the best ways for government antipoverty programs to buffer against the severe levels of resource deprivation observed in the data. As a first pass, this paper provides compelling evidence that there are sizeable returns to providing economic support for society's most financially vulnerable children.

Tables

Table A.1: Estimates of anchoring equations

	Specification (1)	(2)	(3)	(4)	(5)
LW	0.0657 [0.0506, 0.0841]				0.0229 [0.0046, 0.0413]
AP		0.0925 [0.0752, 0.1099]			0.0596 [0.0381, 0.0811]
BE			-0.0464 [-0.0545, -0.0383]		-0.0426 [-0.0528, -0.0324]
BN				-0.0368 [-0.0482, -0.0254]	0.0099 [-0.0040, 0.0238]

Note: Table reports estimates of linear probability model of high school graduation, as specified in equations (2.1) and (5.1). 95% confidence intervals are shown. These estimates are calculated the full sample of PSID-CDS children with available data on scores and high school completion.

Table A.2: Model Estimates I

	Preferences			Variances	
	α_l	$\mu_{\alpha,\theta}$	$\sigma_{\alpha,\theta}$	σ_w	σ_N
	2.313	-2.114	0.560	0.698	1.519
	[1.74, 2.82]	[-2.12, -1.57]	[0.50, 0.61]	[0.66, 0.73]	[1.42, 1.59]

	Coefficients						
	Const	ED_i	PC_i	SE_i	age_i	unemp_i	Y_t
$\log(w_{it})$	1.974	0.086	-0.005	0.086	0.020	-0.014	0.020
	[1.89, 2.11]	[0.08, 0.12]	[-0.00, 0.04]	[0.07, 0.10]	[0.00, 0.03]	[-0.03, 0.00]	[0.00, 0.03]
$\log(N_{it})$	0.808	0.043	0.049	0.405	0.080	0.006	-0.051
	[0.77, 1.21]	[0.04, 0.08]	[0.02, 0.07]	[0.37, 0.42]	[0.06, 0.10]	[-0.01, 0.02]	[-0.08, -0.04]

Note: This table shows estimates for the distribution of mothers' preferences and parameters of the wage and non-labor income process. The final two rows show coefficients on mother's education (ED_i), the mother's score on a passage comprehension test (PC_i) and a self esteem scale (SE_i) administered in the PCG survey, mother's age (age_{it}), the state level unemployment rate (unemp_{it}), and the year (Y_{it}). 95% bootstrap confidence intervals are reported, using 50 resamples with replacement.

Table A.3: Model Estimates II: Fundamental Production Parameters

	Observables		Self-Productivity				Cobb-Douglas Shares			
	ED_i	PC_i	LW_t	AP_t	BE_t	BN_t	$\gamma_{x,0}$	$\gamma_{x,a}$	$\gamma_{\tau,0}$	$\gamma_{\tau,a}$
LW_{t+1}	-0.043	0.044	0.536	0.347	-0.040	0.070	-33.716	-26.421	-79.664	0.103
	[-0.07, -0.04]	[0.02, 0.05]	[0.50, 0.60]	[0.33, 0.40]	[-0.04, -0.01]	[0.04, 0.07]	[-39.51, -31.79]	[-28.82, -23.87]	[-87.28, -73.71]	[0.09, 0.13]
AP_{t+1}	0.030	0.017	-0.023	0.767	-0.035	0.044	-2.217	-0.035	-3.150	0.198
	[0.00, 0.04]	[0.01, 0.03]	[-0.05, -0.02]	[0.66, 0.78]	[-0.04, -0.01]	[0.02, 0.06]	[-2.66, -2.00]	[-0.05, -0.02]	[-3.72, -3.11]	[0.15, 0.20]
BE_{t+1}	-0.009	-0.008	0.164	-0.080	0.925	0.014	-4.627	0.250	-22.987	-0.208
	[-0.03, 0.00]	[-0.02, 0.01]	[0.14, 0.18]	[-0.10, -0.05]	[0.89, 0.96]	[-0.02, 0.03]	[-4.87, -4.34]	[0.22, 0.27]	[-27.79, -21.55]	[-0.22, -0.18]
BN_{t+1}	0.039	-0.056	0.005	-0.003	0.153	0.657	-7.698	0.480	3.048	-1.604
	[0.04, 0.06]	[-0.06, -0.03]	[0.00, 0.03]	[-0.03, 0.00]	[0.16, 0.23]	[0.53, 0.65]	[-8.85, -7.70]	[0.45, 0.53]	[2.60, 3.92]	[-2.02, -1.61]

Note: Production parameters for Letter-Word (LW), Applied Problems (AP), Externalizing Behaviors (BE), and Internalizing Behaviors (BN). The first two columns show the contribution of Mother's education (ED_i) and passage comprehension score (PC_i) to next period skills. The next 4 columns show the cobb-douglas shares defining self-productivity, while the final four columns report the γ parameters that parameterize the Cobb-Douglas shares of money and time investment at each age, for each skill. See equation (4.10) for more details. 95% bootstrap confidence intervals are reported, using 50 resamples with replacement.

Table A.4: Model Estimates III: Contribution of Inputs to Final Skills

	ED_i	PC_i	Money	Time
LW	-0.0002	0.0071	0.0124	0.0759
	[-0.0065, 0.0027]	[0.0023, 0.0081]	[0.0086, 0.0184]	[0.0391, 0.0814]
AP	0.0129	0.0036	0.0200	0.2054
	[0.0044, 0.0152]	[-0.0011, 0.0066]	[0.0115, 0.0277]	[0.0925, 0.2107]
BE	-0.0105	0.0015	0.0978	0.0541
	[-0.0226, -0.0026]	[-0.0032, 0.0091]	[0.0566, 0.1376]	[0.0051, 0.1582]
BN	0.0014	-0.0042	0.0802	0.0232
	[-0.0046, 0.0043]	[-0.0062, -0.0013]	[0.0361, 0.1149]	[0.0020, 0.0673]

Note: Table shows cumulative contribution of inputs to skills in Letter-Word (LW), Applied Problems (AP), Externalizing Behaviors (BE), and Internalizing Behaviors (BN). Skills are anchored their association with the rate of high school graduation. The first two columns show the contribution of Mother's education (ED_i) and passage comprehension score (PC_i). See (4.13) for details of calculation. 95% bootstrap confidence intervals are reported, using 50 resamples with replacement.

Table A.5: Variance Decomposition

	LW	AP	BE	BN
Preferences (ε)	0.5727	0.6000	0.0328	0.0431
Residual (η)	0.3670	0.3096	0.8981	0.4696
Total	0.9398	0.9095	0.9309	0.5127

Note: Table shows the variance of residuals $\overline{\varepsilon}$ and $\overline{\eta}$ as a fraction of the overall variance of skills in Letter-Word (LW), Applied Problems (AP), Externalizing Behaviors (BE), and Internalizing Behaviors (BN). See equation 4.14 for further details.

Table A.6: Model Fit for Select Sample Moments

Moment	Data	Model
$\mathbb{E}[h_{it} \mid Y_t \leq 1996]$	18.5490	18.8080
$\mathbb{E}[h_{it} \mid Y_t > 1996]$	28.0637	26.9636
$\mathbb{E}[h_{it}w_{it} \mid Y_t \leq 1996]$	8.4955	7.8671
$\mathbb{E}[h_{it}w_{it} \mid Y_t > 1996]$	14.7487	15.9037
$\mathbb{E}[LF_{it}]$	0.7505	0.7572
$\mathbb{E}[\log(w_{it})]$	2.0294	2.0526
$\mathbb{E}[\log(N_{it})]$	1.2579	1.0453
$\mathbb{E}[\log(w_{it}) \cdot \mathrm{ED}_i]$	0.3188	0.3742
$\mathbb{E}[\log(N_{it}) \cdot \mathrm{ED}_i]$	0.5390	0.2367
$\mathbb{E}[\log(w_{it}) \cdot \mathrm{PC}_i]$	0.7455	0.6149
$\mathbb{E}[\log(N_{it}) \cdot \mathrm{PC}_i]$	1.6822	1.1814
$\mathbb{E}[\log(w_{it}) \cdot \mathrm{SE}_i]$	0.0422	0.0339
$\mathbb{E}[\log(N_{it}) \cdot \mathrm{SE}_i]$	0.0484	0.0631
$\mathbb{E}[\log(w_{it}) \cdot \mathrm{Age}_{it}]$	0.9014	0.9900
$\mathbb{E}[\log(N_{it}) \cdot \mathrm{Age}_{it}]$	3.0124	3.6324
$\mathbb{E}[\log(w_{it}) \cdot \mathrm{unemp}_{it}]$	-0.0181	-0.0113
$\mathbb{E}[\log(N_{it}) \cdot \mathrm{unemp}_{it}]$	0.0191	0.0555
$\mathbb{E}[\log(w_{it}) \cdot Y_t]$	0.7825	0.8085
$\mathbb{E}[\log(N_{it}) \cdot Y_t]$	0.1299	-0.5339
$\mathbb{V}[\log(w_{it})]$	0.6071	0.5141
$\mathbb{V}[\log(N_{it})]$	3.3203	2.6162
$\mathbb{E}[T_{it}^W \cdot 1]$	4.1234	4.3341
$\mathbb{E}[T_{it}^W \cdot \mathbf{1}\{N_K > 1\}]$	2.1111	1.9146
$\mathbb{E}[T_{it}^W \cdot \mathbf{1}\{Y_t \geq 1997\}]$	0.7034	0.7693
$\mathbb{E}[T_{it}^W \cdot h_{it}w_{it}]$	5.3973	4.7839
$\mathbb{V}[T_{it}^W]$	9.3838	8.7076
$\mathbb{E}[I_{w,it} \cdot 1]$	0.2102	0.1827
$\mathbb{E}[I_{w,it} \cdot \mathbf{1}\{Y_t \geq 1997\}]$	0.0404	0.0495
$\mathbb{E}[I_{w,it} \cdot \log(B_{it})]$	0.4635	0.4300
$\mathbb{E}[I_{w,it} \mid Y_t \leq 1996, h_{it} = 0]$	0.5633	0.6211
$\mathbb{E}[I_{w,it} \mid Y_t > 1996, h_{it} = 0]$	0.4346	0.2970
$\mathbb{E}[I_{w,it} \mid Y_t \leq 1996, h_{it} \leq 20]$	0.5419	0.5531
$\mathbb{E}[I_{w,it} \mid Y_t > 1996, h_{it} \leq 20]$	0.3547	0.2672
$\mathbb{E}[h_{it} \mid Y_t \leq 1996, I_{w,it} = 1]$	6.7960	8.0246
$\mathbb{E}[h_{it} \mid Y_t > 1996, I_{w,it} = 1]$	8.8958	10.3466
$\mathbb{E}[\tau_{97,i}]$	22.7921	19.8172
$\mathbb{E}[\tau_{97,i} \cdot a_{97,k}]$	-25.1536	-34.7381
$\mathbb{E}[\phi_{\tau,97,i}]$	0.1897	0.2180
$Q_{25}(\phi_{\tau,97,i})$	0.1059	0.0772
$Q_{75}(\phi_{\tau,97,i})$	0.2654	0.2656

Table A.7: Model Fit for Production Function Moments

	LW_{02}		AP_{02}		BE_{02}		BN_{02}	
	Data	Model	Data	Model	Data	Model	Data	Model
$\mathbb{V}(\cdot)$	0.8758	0.8436	0.8287	0.9152	20.7955	22.4126	9.9651	11.4923
$\mathbb{C}(\cdot, \text{LW}_{97}),\ \text{age}_{97} \leq 5$	0.5487	0.6702	0.4221	0.4329	0.0608	0.1089	0.1508	-0.1306
$\mathbb{C}(\cdot, \text{LW}_{97}),\ \text{age}_{97} > 5$	0.7686	0.6309	0.6124	0.4826	0.0578	-0.0102	0.0054	-0.0300
$\mathbb{C}(\cdot, \text{AP}_{97}),\ \text{age}_{97} \leq 5$	0.4987	0.5725	0.5964	0.4779	0.0198	0.0136	0.0946	-0.1194
$\mathbb{C}(\cdot, \text{AP}_{97}),\ \text{age}_{97} > 5$	0.4396	0.6112	0.6756	0.5581	0.0581	-0.0305	0.0919	0.0854
$\mathbb{C}(\cdot, \text{BE}_{97}),\ \text{age}_{97} \leq 5$	0.0335	-0.0856	0.0530	-0.1012	0.2662	0.6521	0.2438	0.4814
$\mathbb{C}(\cdot, \text{BE}_{97}),\ \text{age}_{97} > 5$	0.0811	-0.0881	0.0830	0.0319	0.5863	0.7167	0.4951	0.5061
$\mathbb{C}(\cdot, \text{BN}_{97}),\ \text{age}_{97} \leq 5$	-0.0493	0.1631	-0.0496	0.1971	0.0576	0.2520	0.1136	0.3866
$\mathbb{C}(\cdot, \text{BN}_{97}),\ \text{age}_{97} > 5$	-0.0276	0.0145	0.0140	0.0746	0.3603	0.3921	0.4786	0.3702
$\mathbb{C}(\cdot, \log(B_{02})),\ \text{age}_{97} \leq 5$	0.1487	0.1953	0.2285	0.2064	0.0358	0.0601	0.1398	0.0073
$\mathbb{C}(\cdot, \log(B_{02})),\ \text{age}_{97} > 5$	0.1834	0.1896	0.1988	0.1656	0.1967	0.1356	0.1931	0.2824
$\mathbb{C}(\cdot, \log(B_{00})),\ \text{age}_{97} \leq 5$	0.1658	0.2441	0.1840	0.2669	-0.1122	0.0728	-0.0570	0.0202
$\mathbb{C}(\cdot, \log(B_{00})),\ \text{age}_{97} > 5$	0.2039	0.2320	0.1836	0.1867	-0.0169	0.1825	0.0244	0.3825
$\mathbb{C}(\cdot, \log(B_{98})),\ \text{age}_{97} \leq 5$	0.2751	0.2362	0.2042	0.2468	0.0067	0.0817	0.0383	0.0277
$\mathbb{C}(\cdot, \log(B_{98})),\ \text{age}_{97} > 5$	0.2077	0.2731	0.2671	0.2707	0.0743	0.1597	0.1118	0.3484
$\mathbb{C}(\cdot, \log(B_{96})),\ \text{age}_{97} \leq 5$	0.1747	0.1905	0.1234	0.1618	-0.0505	0.0650	0.0441	-0.0300
$\mathbb{C}(\cdot, \log(B_{96})),\ \text{age}_{97} > 5$	0.1684	0.2883	0.1686	0.3026	0.0718	0.1494	0.1251	0.2892
$\mathbb{C}(\cdot, \log(1-h_{02})),\ \text{age}_{97} \leq 5$	-0.1182	-0.0588	-0.1912	-0.1509	-0.0627	0.0600	-0.1552	-0.0335
$\mathbb{C}(\cdot, \log(1-h_{02})),\ \text{age}_{97} > 5$	-0.0640	0.0514	-0.1172	0.0721	-0.0849	0.0006	-0.1175	-0.0869
$\mathbb{C}(\cdot, \log(1-h_{00})),\ \text{age}_{97} \leq 5$	-0.0623	-0.0350	-0.1469	-0.1510	0.0333	0.0536	0.0620	-0.0277
$\mathbb{C}(\cdot, \log(1-h_{00})),\ \text{age}_{97} > 5$	-0.0896	0.0506	-0.1351	0.0792	0.0151	0.0115	-0.0548	-0.0770
$\mathbb{C}(\cdot, \log(1-h_{98})),\ \text{age}_{97} \leq 5$	-0.1417	-0.0097	-0.1693	-0.0994	-0.0903	0.0319	-0.1540	-0.0460
$\mathbb{C}(\cdot, \log(1-h_{98})),\ \text{age}_{97} > 5$	-0.1685	0.0545	-0.1838	0.0283	-0.0426	0.0505	-0.0281	0.0100
$\mathbb{C}(\cdot, \log(1-h_{96})),\ \text{age}_{97} \leq 5$	-0.2336	-0.0910	-0.2220	-0.1392	0.0045	0.0124	-0.0916	0.0135
$\mathbb{C}(\cdot, \log(1-h_{96})),\ \text{age}_{97} > 5$	-0.1579	-0.2045	-0.0889	-0.3142	-0.0261	-0.0495	-0.0800	-0.0757
$\mathbb{C}(\cdot, \phi_{\tau,97})$	0.1005	0.2851	0.0964	0.3289	-0.1024	0.0866	-0.1234	0.1205
$\mathbb{C}(\cdot, \text{ED})$	0.1932	0.1375	0.2009	0.2606	-0.0410	-0.0272	-0.0239	0.0094
$\mathbb{C}(\cdot, \text{PC})$	0.2257	0.5242	0.2454	0.2408	0.0229	0.0556	0.0401	-0.1473

Table A.8: Aggregate Results for Two Policy Reforms

	Total Income	Hours	Δ HSG	CEV
Baseline	24.8492	23.8331	0.0000	0.0000
Basic Income	24.1770	17.6589	0.0019	0.0014
Optimal Reform	24.8265	22.5033	0.0041	0.0032

General Model and Solution

In this section, I derive the model solution for an arbitrary number of skills, N_θ, and an arbitrary number of children N_K. Let $k = 1, 2, 3, .., N_K$ index each child in ascending order of birth. In this section I assume that birth years are exogenously given and known to the mother. However, as we move through the solution it should be clear that extending the model to relax this assumption need not forbid the key simplification of additive separability in $\log(\theta)$, the skill vector. In fact, this is shown in greater detail in Brown, Flinn, and Mullins (2015), which includes endogenous fertility and marriage decisions. Let $\mathcal{B} = \{b_1, b_2, ..., b_{N_K}\}$ indicate the year in which each child is born. As before, every child matures at age A. I let the problem begin, as before, with the birth of the first child. Therefore we can set $b_1 = 0$, and set the terminal period of the problem at $T_M = b_{N_K} + A$. Now, θ refers to the full vector of skills for each child, and is therefore of dimension $N_\theta \times N_K$. We let $\theta_{k,j}$ refer to the jth skill of the kth child in the family and, similarly, θ_k is the full skill vector for child k. Finally, let $a_k(t) = t - b_k$ indicate the age of child k. Noting that age is collinear in time, I suppress the dependance of a_k on t for notational simplicity.

Preferences and Technology

To solve the problem, we must extend preferences to include multiple children, which we do simply as:

$$u(c, l, \theta) = \alpha_c \log(c) + \alpha_l \log(l) + \sum_{k:\ a_k \geq 0} \alpha_\theta \log(\theta_k) \tag{B.1}$$

$$V_{T_M}(\theta) = (1-\beta)^{-1} \sum_k \alpha_\theta \log(\theta_k) \tag{B.2}$$

Next, I have to take a stand on the rivalrous nature of time and monetary investment. Ideally, one could assume the existence of public investment categories as well as categories that each child would benefit from privately. In the case of time investment, this would be empirically plausible since categories of time use are observable[8]. Further, this setup can handle an arbitrary number

[8] Less so, for expenditure categories.

of investment categories: we will see that each would be determined by a proportional investment rule. Yet this exact property removes this assumption of any empirical content in our context, since child outcomes are driven through changes in the log of total income (B_t) and log of total leisure hours ($1 - h_t$). When investment rules are proportional to total income and total leisure time, we can derive labor supply, program participation, and child outcomes in terms of aggregates that depend only on the total cobb-douglas shares of each category. This logic extends to the case of multiple children. If time use is rivalrous, it is true that a child with siblings receives a lesser share of spare leisure hours than an only child, *ceterus paribus*, however this proportion bears no impact once we take logs (in effect, looking at percentage changes in investment). Thus, I assume in this paper that there is only one monetary investment and one time investment category, and that each is non-rivalrous across siblings.

Model Solution

Given this set of assumptions, we can write the dynamic program in the following fashion:

$$V_t(\theta_t, S_t, \eta_t) = \max_{c,l,x,\tau,h\in\mathcal{H},p} \Big\{u(c, l, \theta_t, p) + \beta\mathbb{E}[V_{t+1}(\theta_{t+1}, S_{t+1}, \eta_{t+1}) \; |S_t, h, p]\Big\} \tag{B.3}$$

Subject to the constraints:

$$c + x \leq \mathbf{B}(s_t, h, p) \tag{B.4}$$

$$\tau + l + h = 1 \tag{B.5}$$

$$\theta_{k,t+1} = \delta_{x,a_k} \log(x) + \delta_{\tau,a_k} \log(\tau) + \delta_{\theta,a_k} \log(\theta) + \eta_{k,t}, \qquad \forall k : \; a_k \geq 0 \tag{B.6}$$

Note that in this general formulation, the vector S_{t+1} is permitted to evolve according to the current state S_t in addition to the labor supply (h) and program participation (p) decisions of the mother. Some of this model's convenient representation could quite conceivably break if the evolution of S_t was further allowed to depend on investments (x, τ). I first propose the following simplification of the model and show that it holds. As before, the key is that the value function is additively separable in $\log(\theta)$:

$$V_t(\theta, S_t, \eta_t) = \sum_{k=1}^{N_k} \alpha_{V,a_k} \log(\theta_{k,t}) + \sum_{k:a_k \geq 0} \alpha_{V,a_k+1} \log(\eta_{k,t}) + \nu(S_t) \tag{B.7}$$

$$\nu(S_t) = \max_{h \in \mathcal{H}, p} \left\{ \overline{\alpha}_{c,t} \log(\mathbf{B}(S_t, h, p)) + \overline{\alpha}_{\tau,t} \log(1-h) + \beta \mathbb{E}[\nu(s_{t+1}) \mid S_t, h, p] \right\} \tag{B.8}$$

$$\overline{\alpha}_{c,t} = \alpha_c + \beta \sum_{k:\ 0 \leq a_k < A} \alpha_{V,a_k+1} \delta_{x,a_k} \tag{B.9}$$

$$\overline{\alpha}_{\tau,t} = \alpha_c + \beta \sum_{k:\ 0 \leq a_k < A} \alpha_{V,a_k+1} \delta_{\tau,a_k} \tag{B.10}$$

$$\alpha_{V,a} = \alpha_\theta + \mathbf{1}\{0 \leq a_k < A\} \cdot \beta \alpha_{V,a+1} \delta_{\theta,a} \tag{B.11}$$

$$x_t = \frac{\beta \sum_{k:\ 0 \leq a_k < A} \alpha_{V,a_k+1} \delta_{x,a_k}}{\overline{\alpha}_{c,t}} \mathbf{B}(S_t, h, p) \tag{B.12}$$

$$\tau_t = \frac{\beta \sum_{k:\ 0 \leq a_k < A} \alpha_{V,a_k+1} \delta_{\tau,a_k}}{\overline{\alpha}_{l,t}} (1-h) \tag{B.13}$$

We prove this by first showing that the recursion holds. That is, assume this form holds for V_{t+1} and show that it is preserved at time t. The problem can be stated as:

$$\begin{aligned} V_t(\theta, S_t, \eta_t) = \max_{c,l,x,\tau,h,p} & \Bigg\{ \alpha_c \log(c) + \alpha_l \log(l) + \sum_{k:\ a_k \geq 0} \alpha_\theta \log(\theta) \\ & + \beta \mathbb{E}\left[\nu(S_{t+1}) + \sum_k \alpha_{V,a_k+1} \log(\theta_{k,t+1}) + \sum_{0 \leq a_k+1 < A} \alpha_{V,a_k+2} \log(\eta_{k,t+1}) \mid S_t, h, p \right] \Bigg\} \end{aligned} \tag{B.14}$$

subject to the constraints given above. First, we can substitute in the production function to get:

$$\begin{aligned} V_t(\theta, S_t, \eta_t) = \max_{c,l,x,\tau,h,p} & \Bigg\{ \alpha_c \log(c) + \alpha_l \log(l) + \sum_{k:\ a_k \geq 0} \alpha_\theta \log(\theta_{k,t}) \\ & + \underbrace{\sum_k (\alpha_\theta + \mathbf{1}\{0 \leq a_k < A\} \cdot \alpha_{V,a_k+1} \delta_{\theta,a_k})}_{=\alpha_{V,a_k}} \log(\theta_{k,t}) \\ & + \beta \sum_{k:\ 0 \leq a_k < A} \alpha_{V,a_k+1} [\delta_{x,a_k} \log(x) + \delta_{\tau,a_k} \log(\tau) + \log(\eta_{k,t})] \\ & + \beta \mathbb{E}\left[\nu(S_{t+1}) + \sum_{0 \leq a_k+1 < A} \alpha_{V,a_k+2} \log(\eta_{k,t+1}) \mid S_t, h, p \right] \Bigg\} \end{aligned} \tag{B.15}$$

As is indicated in the second line of this equation, this step is sufficient to define the recursion for $\alpha_{V,a}$, the value derived from $\log(\theta)$ for a child at age a. Next, we inspect the first order conditions for τ and x, subject to choices of h and p. These yield:

$$\frac{\alpha_c}{c} = \frac{\beta \sum_{k:\ 0 \leq a_k < A} \alpha_{V,a_k} \delta_{x,a_k}}{x} \tag{B.16}$$

$$\frac{\alpha_l}{l} = \frac{\beta \sum_{k:\ 0 \leq a_k < A} \alpha_{V,a_k} \delta_{\tau,a_k}}{\tau} \tag{B.17}$$

$$\tag{B.18}$$

Rearranging these equations gives the proportional investment rules shown in (B.12) and (B.13). Substituting those rules into the value function (B.15) and collecting terms gives the final expression of the value function in (B.7) and (B.8). We can complete this exposition for the solution by noting that the terminal period value function $V_{T_M}(\theta)$ also keeps this additive form, and hence we have the necessary conditions to initiate the recursion.

Description of the Transfer Functions

In this section I describe the computation of the transfer functions (T^F, T^A, T^T). The details of this section very closely follow Chan (2013), which should be consulted for further details.

Welfare

The transfer function T^A includes a benefit computation, and an eligibility test:

$$T^A_{it} = \text{El}^A_{it} \times \text{Ben}^A_{it} \tag{C.1}$$

Where

$$\text{El}^A_{it} = \mathbf{1}\{L_{it} \leq \mathcal{L}_{it}\} \times \mathbf{1}\left\{E_{it} + N_{it} < r_{Agit} e_{Ait}\right\} \times \mathbf{1}\left\{(E_{it} - D_{Aeit})(1 - R_{Aeit}) + N_{it} < r_{Anit} e_{Ait}\right\}. \tag{C.2}$$

Eligibility above is defined as the combination of a time limit, a net income test, and a gross income test. Both tests compare income with a need standard, e_{Ait} which is inflated by some rate (r_{Agit}, r_{Aeit}). Second, the computation of net income involves a fixed disregard on earnings, D_{Aeit} and a percentage disregard. Benefit computation follows similarly:

$$\text{Ben}^A_{it} = \max\{G_{Ait} - (E_{it} - D_{Abit})(1 - R_{Abit}) - N_{it}, 0\} \tag{C.3}$$

The payment standard G_{Ait} sets the generosity of the program when no other sources of income are reported, while the dollar and percentage disregards (D_{Abit}, R_{Abit}) combine to determine net income. Importantly, these policy parameters are a function of the mother's state of residence, the number of dependant children and the year. In this model, these variables are all a function of the mother-year index, it.

Food Stamps

Similarly to welfare, the food stamp transfer function T^F can be written as:

$$T^A_{it} = \text{El}^F_{it} \times \text{Ben}^F_{it} \tag{C.4}$$

Where

$$\text{El}^F_{it} = \mathbf{1}\left\{E_{it} + N_{it} < 1.3 e_{Fit}\right\} \times \mathbf{1}\{\underbrace{0.8E_{it} + N_{it} + \text{Ben}^A_{it} - 134}_{=\text{Net}^F_{it}} < e_{Fit}\}. \tag{C.5}$$

In the above expression, e_{Fit} is referred to as the poverty guideline, and the net income includes a standard 20% disregard and \$134 deduction. While the true food stamp benefit formula technically allows for further deductions for child care expenses, child support payments, and shelter expenses, I have insufficient data to calculate these deductions. Finally, given a maximum benefit G_{Fit}, the benefit calculation is:

$$\text{Ben}_{it}^F = \max\left\{G_{Fit} - 0.3\text{Net}_{it}^F, 0\right\}. \tag{C.6}$$

Data Sources for Program Rules

To summarize, the parameter vector $\mathcal{P}_{it}^A$ can be written as

$$\mathcal{P}_{it} = \{r_{Agit}, r_{Aeit}, e_{Ait}, D_{Aeit}, R_{Aeit}, G_{Ait}, D_{Abit}, R_{Abit}, \mathcal{L}_{it}\},$$

while $\mathcal{P}_{it}^F$ can be summarized as

$$\mathcal{P}_{it}^F = \{e_{Fit}, G_{Fit}\}.$$

Parameters on welfare that comprise $\mathcal{P}_{it}^A$ and $\mathcal{P}_{it}^F$ were collected from the Urban Institute's TRIM3 simulation database[9] for years 1985-2011. In addition, since rules on net income calculations were much more simple prior to 1993, I use a 30% disregard across all states [10]. Mothers were merged with program rules based on their state of residence, the year, and the number of children in their household of age 17 or younger.

Taxes

Taxes consist of a federal and a state computation. When earned income is sufficiently low, $\mathcal{T}^T$ will arrive in the form of a net payment (when income tax obligations are exceeded by the EITC). In theory, the relevant parameters to compute taxes include those that define the federal and state EITC programs, state and federal deductions and exemptions, and the marginal income tax rate with their corresponding brackets for state and federal income tax. In practice, I use the TAXSIM model of Feenberg and Coutts (1993), to approximate the tax function. Given the relevant year, state, and family size (in our model these are all exogenous functions of the index, *it*), TAXSIM computes $\mathcal{T}_{it}^T(e)$ for any given earnings level. Thus, for each *it* in my sample, I compute $\mathcal{T}_{it}^T(e)$ for earnings levels e on a grid, using increments of \$100, between \$0 and \$100,000[11]. Using this grid, the tax function is approximated using linear interpolation between these grid points.

[9] Source: http://trim3.urban.org/

[10] This approach is taken also in Chan (2013)

[11] This suits as a reasonable upper bound in my sample

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