Quasi-Structural Estimation of a Model of Child Care Choices and Child Cognitive Ability Production

Raquel Bernal[1]
Department of Economics and
IPR Faculty Fellow
Northwestern University

Michael P. Keane
Department of Economics
Yale University

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Abstract

This paper evaluates the effects of maternal vs. alternative care providers' time inputs on children's cognitive development using the sample of single mothers in the National Longitudinal Survey of Youth. To deal with the selection problem created by unobserved heterogeneity of mothers and children, we develop a model of mother's employment and child-care decisions. Guided by this model, we obtain approximate decisions rules for employment and child care use, and estimate these jointly with the child's cognitive ability production function – an approach we refer to as "quasi-structural." This joint estimation implements a selection correction.

To help identify our selection model, we take advantage of the substantial and plausibly exogenous variation in employment and child-care choices of single mothers generated by the variation in welfare rules across states and over time – especially, the large changes created by the 1996 welfare reform legislation and earlier State waivers. Welfare rules provide natural exclusion restrictions, as it is plausible they enter decision rules for employment and day care use, while not entering the child cognitive ability production function directly.

Our results imply that if a mother works full-time, while placing a child in day care, for one full year, it reduces the child's cognitive ability test score by roughly 2.7% on average, which is 0.14 standard deviations of the score distribution. However, we find evidence of substantial observed and unobserved heterogeneity in the day care effect. Negative effects of day care on test scores are larger for better-educated mothers and for children with larger skill endowments.

[1] Corresponding author: rbernal@northwestern.edu

1. Introduction

The effect of home inputs on child cognitive development has been widely analyzed, especially in the psychology and sociology literature. Much of the prior work has fussed on effects of maternal time vs. alternative provider time, and the effects of goods inputs or household income. Economists have recently become quite interested in these questions. One motivation comes from recent studies in the human capital literature, such as Keane and Wolpin (1997, 2001, 2006) and Cameron and Heckman (1998), which suggest that educational attainment and labor market outcomes in later life (i.e., wages and employment) are largely determined by skill "endowments" that are already in place by around ages 14-16. But the early determinants of these teenage skill "endowments" remain largely a black box. Hence, the human capital literature needs to place more emphasis on investments in children at early ages, including parental time and goods inputs into child development.

Extensive research has shown that children's early cognitive achievement is a strong predictor of a variety of outcomes later in life: the high achievers are more likely to have higher educational attainment and higher earnings; and less likely to have out-of-wedlock births, be on welfare or participate in crime. Bernal and Keane (2006) review this literature, and also show, using the National Longitudinal Survey of Youth (NLSY), that test scores as early as ages 4 to 6 are strongly correlated with completed education for children of single mothers.[2] For this reason, understanding the determinants of cognitive ability at early ages would appear to be critical for the design of public policy aimed at improving subsequent labor market outcomes. However, the question of what determines children's cognitive achievement in general, and the role of parental time and goods inputs in particular, remains largely unresolved.

Unfortunately, two key problems hamper research in this area: (1) the paucity of good data on inputs into child cognitive development at early ages, and (2) the difficult selection problem that arises because inputs into child development may be correlated with unobserved characteristics of parents and children. In this paper, we tackle a small aspect of this general problem, by looking at the effect of maternal vs. alternative care provider time inputs, and household income, on child cognitive ability test scores recorded at ages 4-6. For this purpose, we use data on single mothers from the 1979 NLSY.

[2] They find, for example, that a 1% increase in the PIAT math test score at age 6, holding parental background variables like mother's education and IQ fixed, is associated with an increase in educational attainment (measured at age 18 or later) of approximately .019 years. For reading scores the figure is .025 years.

In studying the effect of maternal time inputs on child outcomes, two sources of selection bias are of key concern: (1) Women that work/use child care may differ systematically from those that do not; (2) Child cognitive ability may itself influence a mother's decisions about work/daycare. To illustrate problem (1), suppose high-skilled women are more likely to have high cognitive ability children, and also more likely to work/use day care. Then, a statistical analysis may spuriously attribute a positive effect of maternal employment/child care use on child cognitive outcomes. To illustrate problem (2), suppose mothers of low ability endowment children try to compensate by spending more time with them, so that mothers of low ability endowment children work less. Again, the estimated effect of maternal employment/child care on child cognitive outcomes would be upwardly biased. Clearly, these sample selection issues make evaluation of the effects of women's decisions on child outcomes very difficult.

The data on single mothers in the NLSY79 provide an important opportunity to address these selection problems, and to obtain more reliable estimates of effects of maternal work/day care use on child outcomes. A subset of these women was affected by the 1996 reform of the U.S. welfare system that created the Temporary Aid to Needy Families (TANF) program, or by earlier State welfare waivers, and/or by substantial increases in day care subsidy spending by the Child Care Development Fund (CCDF). These rule changes had strong effects on the incentives for single mothers to work and use child-care. In fact, the percent of single mothers who work increased from 67% in 1992 to 79% in 2001, with even larger increases for certain subgroups.[3]

Thus, for women in the NLSY79 whose children reached ages 4-6 after the start of the reforms, there was a strong and plausibly exogenous increase in their incentive to work/use day care prior to our observations on their children's test scores. Women whose children reached ages 4-6 prior to the start of the reforms were not affected by these changes. This source of variation helps identify the effect of maternal work/day care use on child outcomes.[4]

While this discussion gives an intuition for our approach, it may seem to suggest a simple before-and-after welfare reform comparison of test score outcomes and levels of maternal work – as in the natural experiment/instrumental variable (IV) literature. This is, in fact, a gross over-

[3] From 57% to 78% for never married single mothers, 40% to 61% for those with low education, 59% to 78% for those with children aged 0-5, 34% to 67% for those with 3+ children, and 57% to 76% for African-Americans.
[4] Our description may suggest there was point in time when welfare rules simply became stricter. But this is just an oversimplification to facilitate exposition. A key aspect of the 1996 welfare reform, and of earlier welfare waivers, was to give States greater flexibility in setting rules. Thus, there was a great deal of heterogeneity across the U.S. States in the timing of welfare rule changes, and in the nature of the changes. See, e.g., Fang and Keane (2004) for an extensive discussion of these cross State differences in policies.

simplification of the approach we actually implement. As Rosenzweig and Wolpin (2000) stress in a range of examples, what IV estimates depends on what one controls for. For example, welfare reform may have altered not just maternal time inputs, but also goods inputs. Thus, in order to interpret our estimates, we need to consider a particular theoretical model, including a specification of the child cognitive ability production function, and the relation between this and the outcome equation we actually estimate (i.e., due to data limitations, not all inputs into the production function are observable, complicating interpretation). We discuss this in section 4.1.

Hence, our empirical work is guided by a structural model of mother's employment and child care use decisions that we describe in section 4.1. Guided by this model, we obtain approximate decisions rules for employment and child care use, and estimate these jointly with the child's cognitive ability production function and the mother's wage function – an approach we refer to as "quasi-structural." In our selection model, welfare rules provide natural exclusion restrictions, as it is plausible that they enter the decision rules for employment and day care use, while not entering the child cognitive ability production function. We use local demand conditions as additional instruments (i.e., exclusions), as it seems natural these enter the decision rules for work/day care but not the cognitive ability production function. Our results imply that one full year of full-time work and full-time day care reduces a child's cognitive ability test score by roughly 2.7% on average, which is 0.14 standard deviations of the score distribution.

This result is similar to a –3.2% annual effect estimate we obtain using a single equation IV approach, using the same welfare rule and local demand instruments. Each approach relies on somewhat different identifying assumptions; particularly in terms of the exact form of the decision rules for work and child care (whose form the IV approach leaves implicit). Hence, each implements a somewhat different correction for selection of different types of children into day care. Thus, it is comforting that results are so similar across the two approaches.

A key advantage of the quasi-structural approach over linear IV is that we can accommodate unobserved heterogeneity in effects of maternal work and child care use on child outcomes. We find evidence of substantial observed and unobserved heterogeneity in the day care effect. Negative effects of day care on test scores are larger for better-educated mothers and for children with larger skill endowments.

Another advantage is that explicitly estimating the work and child care decision rules, and including the mother's wage function, as a system, we achieve a rather substantial efficiency gain. Indeed, the standard error on the cumulative childcare use coefficient in the log test score equation falls by a factor of 7.4, giving us much greater confidence in the estimated effect size.[5] This occurs in part because wage equation residual conveys information about the mother's unobserved skill endowment, and hence about the unobservable in the test score equation.

On the other hand, a disadvantage of the quasi-structural approach is that mis-specification of the joint distribution of the unobservables across the four equations of the system could lead to inconsistency.[6] Another advantage of single equation IV is its relative simplicity of implementation, which, in Bernal and Keane (2006) enables us to examine a very large number of alternative specifications in which maternal work and day care use affect child cognitive outcomes in different ways.[7] Given the time required to estimate the quasi-structural system, such extensive testing is not practical here.

A key difference between either a quasi-structural or single equation IV approach and a full solution/full information maximum likelihood (FIML) is that FIML requires one to fully specify the process by which agents form expectations of the forcing variables. For instance, we could assume perfect foresight regarding future welfare rules, or myopia (i.e., each rule change comes as a surprise), or rational expectations (i.e., agents know the process generating the rules). The IV and quasi-structural approaches allow us to sidestep this issue in estimation.

This has both advantages and disadvantages. While it may provide more robust estimates, the failure to fully specify the model creates problems when it comes to policy simulation. For instance, a change in welfare policy may have very different effects on maternal work/day care use, and goods inputs, depending on whether it is perceived as permanent or transitory.[8] Thus, to simulate effects of policy changes on maternal decisions and child outcomes, we can't avoid making assumptions (either explicitly or implicitly) about expectations.[9]

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[5] Using linear IV, the coefficient on quarters of child care is -.00807 with a standard error of .00333 (t = -2.42). Using a special case of the quasi-structural model, that assumes homogeneous effects, the coefficient is -.00698, with a standard error of .00045 (t=15.5).

[6] Another approach that might be less sensitive to this problem is to estimate the 4-equation system by method of moments. Of course, MOM has its own problems, such as loss of efficiency relative to ML estimation of the system, and potential sensitivity of results to choices of instruments and weighting matrices.

[7] For instance, it may be cumulative inputs that matter, analogous to the typical Mincer earnings specification where cumulative schooling and work experience affect current human capital, or it may be average inputs, or more recent inputs, that matter. Or maternal work and day care may have larger effects if they occur at earlier or later child ages. Or, different types of day care, such as formal vs. informal, may have different impacts on child outcomes.

[8] See Keane and Wolpin (2002a, b) for a detailed discussion of these issues.

[9] More subtly, the perceived persistence of welfare policy changes may influence what IV and quasi-structural estimates of maternal time effects mean. For example, a permanent rule change that leads to a permanent increase in

Our study of single mothers extends earlier work by Bernal (2003) on children of married women in the NLSY. Using a fully structural approach, she found that one-year of maternal full-time work and child-care results in a 2% reduction in child cognitive ability test scores. A key motivation of our work was to see if that result generalized from married to single mothers. Our estimate for single mothers is larger (3%), but the similarity of the results is still striking.

Bernal (2003) relied on very different exclusion restrictions from those used here. She treats age profiles of husband and wife earnings as exogenous, in the sense that (1) only the parents' skill endowments, and not their age, affect the skill the child inherits, and (2) only skill endowments and permanent income of mothers and husbands, and not short run fluctuations in household income (e.g., due to movement along the wage/age path) affect their investment in children. Thus, otherwise identical women who have children when they or their husbands are at different points in the life-cycle wage path will have different incentives to work. This creates exogenous variation in work/child care use that helps to identify the effects of maternal time inputs.[10] While we find this approach to identification appealing, we think the welfare policy rules we use here are more appealing, as their exogeneity is less subject to challenge.

Obviously, aside from the technical advantage that arises because of the presence of highly plausible instruments (i.e., the welfare rule changes), the study of single mothers is of special policy interest as well, given the huge welfare policy changes that have substantially increased their work and day care usage in recent years. Since we find that maternal work and day care use has negative effects on test scores for children of single mothers, it suggests an aspect of cost of these policies that needs to be considered when evaluating their overall success.

2. Literature Review

Many prior studies, mostly in the developmental psychology literature, have used NLSY data to assess effects of maternal employment or child care use on child cognitive development. For reviews of this literature see Love et al (1996), Blau (1999), Lamb (1996), Haveman and Wolf (1994) and Ruhm (2002). We also summarize this literature in Bernal and Keane (2006).

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work effort might induce mothers to increase goods inputs into children to compensate, or to increase "quality" time as a share of total time, etc.. A transitory rule change might not have such effects. Thus, the estimated effect of maternal time inputs may differ depending on the perceived persistence of the rule change that induced them.

[10] Indeed, in the NLSY data Bernal (2005) used, for otherwise similar looking couples, women do work more during the early years of a child's life if the child was born when the husband is younger (so his wage is lower and the woman has less "other" income), or when the woman is older (so her wage rate is higher).

As we note, most these studies present simple correlations between inputs and child outcomes and do not include additional controls for family characteristics and/or child characteristics. In most cases, no control for self-selection of children into child care is implemented.[11]

The results of the prior literature are quite inconclusive. Of the papers that use the NLSY data to assess effect of maternal employment on child cognitive outcomes, roughly a third report positive effects, a third negative effects, and the remainder either insignificant effects or effects that vary depending on the group studied or the timing of inputs. Similarly, of the papers that evaluate effects of daycare on child outcomes, effects range from positive to negative and are in most cases either insignificant or vary with the specific sample used or the quality of daycare.

The diversity of these results may stem from the wide range of specifications that are estimated, and the common limitation of failing to control for selection bias. To make our exposition of the literature more clear, it is useful to have a specific framework in mind.[12] Consider the following equation, interpretable as a cognitive ability production function:

$$\ln S_{ijt} = \alpha_1 T_{ijt} + \alpha_2 C_{ijt} + \alpha_3 G_{ijt} + \alpha_4 X_{ijt} + \mu_j + \delta_{ij} + \varepsilon_{ijt} \qquad (1)$$

Here S_{ijt} is the cognitive outcome for child i of mother j at age t (i.e., a test score). T_{ijt} is a measure of the maternal time inputs up through age t. This may be a scalar, as in a cumulative specification, or one where only average or current inputs matter. Or, it may be a vector, if inputs at different ages have different effects. Similarly, C_{ijt} is a measure of nonmaternal time input (i.e., child care), and G_{ijt} represents goods inputs. Next, X_{ijt} is a set of controls for the child's initial skill endowment. This may include variables such as the mother's age, education, IQ, etc. (to capture inherited ability endowment), and initial characteristics of the child such as gender, race, and birthweight. The error components μ_j and δ_{ij} are family and child effects, which capture parts the *unobserved* skill endowment of the child. Finally, ε_{ijt} is a transitory error that may be interpreted as measurement error inherent in the test plus (or in recording the test result).

While (1) is the general setup that, at least implicitly, seems to underlie most of the papers in the literature, none actually estimate this equation, and many estimate equations that seem quite far from it. One fundamental problem is that the maternal time input T and the goods

[11] See for example, Burchinal et al. (1996) and Parcel and Menaghan (1990).

[12] Todd and Wolpin (2003, 2005), Rosenzweig and Wolpin (1994) and Rosenzweig and Schultz (1983) also discuss estimation and specification of cognitive ability production functions, and raise many of the issues we will raise here. We focus specifically on issues that arise in estimating effects of parental time, child care and goods inputs on child development.

inputs G are not directly observed. Most papers ignore this problem, simply using maternal employment or child care use in place of maternal time.[13] Also, most papers use one or the other of these variables, and do not examine both. Similarly, most papers simply ignore G.[14] A few attempt to proxy for it using household income or the NLSY's "HOME" environment index. The later is problematic because it based not just on goods inputs but also maternal time inputs. To our knowledge, only James-Burdumy (2005) discusses the relationship between her estimating equation a child ability production function and by pointing out the difficulty in interpreting estimates when proxies are used for the maternal time and goods inputs.

Second, most papers in the literature have simply used current inputs (i.e., maternal time, child care and goods used at the time of the outcome). This is a strong assumption, especially in light of the tradition in the human capital literature that cumulative inputs matter. Of course, one could have a more general specification according to which the whole history of inputs since childbirth matters for the child's outcome at time t. Most papers do not discuss the implications of their assumptions regarding timing of inputs.[15] We will discuss these issues in Section 4.

Finally, most papers in the literature estimate equation (1) by OLS, ignoring the potential endogeneity of the inputs – that is, the potential correlation of the maternal work and day care use decisions, and the goods inputs, with the unobserved ability endowments, μ_j and δ_{ij}. A few recent studies have tried to overcome this problem by using either: (1) an extensive set of explanatory variables to proxy for unmeasured endowments (2) child or family fixed effects, or "value added" models, and/or (3) instrumental variables.

Consider first studies that could be classified as using extensive controls. These include Han et al (2001), Baydar and Brooks-Gunn (1991), Parcel and Menaghan (1994), Vandell and Ramanan (1992) and Ruhm (2002). They use an extensive set of observable characteristics of the child and mother, including the mother's AFQT score - a measure of IQ available in the NLSY. In spite of this, the results of these papers are inconclusive. For example, Baydar and Brooks-Gunn (1991) find maternal employment in the child's first year negatively affects cognitive

[13] For example, Vandell & Ramanan (1992) estimate the effect of maternal employment on child cognitive outcomes but do not include child care arrangements as an additional input. Similarly, Caughy, DiPietro and Strobino (1994) assess the effect of child care participation but do not include maternal time inputs in their specification.

[14] For example, Baydar and Brooks-Gunn (1991) estimate the effects of both maternal employment and child care arrangements but do not include goods/services (or a proxy such as household income) in the production function.

[15] Notable exceptions are Blau (1999) and Duncan-NICHD (2003). Some papers use maternal employment (and/or child care use) at different years after childbirth, but do not discuss implications in terms of the underlying production function (e.g., Waldfogel et al. (2002), Vandell and Ramanan (1992), Baydar and Brooks-Gunn (1991)).

outcomes, while Vandell and Ramanan (1992) report positive effects of early employment on math scores, and positive effects of current employment on reading scores. Ruhm (2002) finds significant negative effects of maternal employment on math scores, while Parcel and Menaghan (1994) find small positive effects of maternal employment on child cognitive outcomes.

Next, consider studies that use fixed effects. Chase-Lansdale et al. (2003) use child fixed effects models to assess the effect of maternal employment on children's outcomes. They analyzed 2402 low-income families during the recent era of welfare reform. Their results suggest that mothers' transitions off welfare and into employment are not associated with negative outcomes for preschoolers. They note, however, that this approach does not account for endogeneity of these transitions, and they do not attempt to use the changes in welfare rules as instruments for maternal employment as we do here.

James-Burdumy (2005) estimated household FE models using a sample of 498 sibling children in the NLSY. She finds the effect of maternal employment varies depending on the assessment used and the timing of employment.[16] The use of sibling differences eliminates the mother (or household) fixed effects μ_j from (1) but does not eliminate the child fixed effect δ_{ij}. It is plausible that mothers make time compensations for children depending on their ability type. In this case, a household fixed effect model is not be appropriate, since maternal employment is correlated with the sibling specific part of the cognitive ability endowment. In addition, the FE estimator requires that input choices are unresponsive to prior sibling outcomes. If inputs to child *i'* are responsive to outcomes for child *i*, then ε_{ijt} will be correlated with those inputs.

Blau (1999) and Duncan and NICHD (2003) both study the effects of child care usage and child care quality on child outcomes. They use very similar methodologies, including both a wide range of proxies for unmeasured child ability endowment (like mother's AFQT and education), controls for many aspects of the home environment, and use of various fixed effects and value added specifications.[17] The main difference in the studies is that Blau (1999) uses the NLSY while Duncan uses the NICHD Study of Early Child Care. Blau (1999) concludes that

[16] According to James-Burdumy (2005)'s fixed effects estimates in her Table 5, an increase in maternal work from 0 to 2000 hours in year 1 of the child's life reduces the PIAT math score (measured at ages 3 to 5) by (-.00117)×2000 = -2.34 points. This is similar to the effect we estimate for one year of full-time work (-3.0%). On the other hand, she finds no significant effect of maternal employment after the first year, so her estimate of the effect of five years of full-time employment is not nearly as large as ours.

[17] In the value-added approach, the test score in period t (S_{ijt}) is a function of the outcome in period $t-1$ and the inputs in period t, the idea being that the lagged test score proxies for the child's ability at the start of a period.

"child care inputs experienced during the first three years of life have little impact on … child outcomes …" while Duncan finds a modest positive effect of improved child care quality.[18]

From our perspective, a key difficulty in interpreting the Blau and Duncan results is that both studies control for *G* using the HOME environment index, which combines survey items that measure both goods inputs (e.g., books in the home), and time inputs (e.g., how often the child is read to, eats meals with the parents, or talks with the mother while she does housework). Thus, the coefficients on whether the mother works or uses day care measure the effect of those variables holding the HOME index fixed. In contrast, we are interested in the total impact of the maternal time input on child outcomes. This should include how a decline in the time input (resulting from increased work or day care use) affects time spent reading to the child and so on.

The Blau (1999) and Duncan-NICHD (2003) papers contain useful discussions of the limitations of fixed effects and value added specifications. As they point out, neither provides a panacea for dealing with unobserved child ability, as both models rely on assumptions that are in some cases stronger than OLS. For example, the household FE estimator requires that input choices are unresponsive to the child specific part of the ability endowment. The value added model runs into the problem that estimates of lagged dependent variable models are inconsistent in the presence of fixed effects like μ_j and δ_{ij}.[19] Neither approach, nor child fixed effects, deals with the endogeneity problem that arises because current inputs may respond to lagged test score realizations. An IV approach is necessary to deal with these endogeneity problems.

Only two papers have attempted to use IV. These are Blau and Grossberg (1992) and James-Burdumy (2005). Both look at effects of maternal work on child outcomes, and do not examine effects of maternal day care use *per se*. More importantly, both papers suffer from the problem that the instruments are extremely weak.

For instance, Blau and Grossberg (1992) use work experience prior to childbirth as the instrument for maternal employment.[20] It is questionable whether this variable is uncorrelated with the child cognitive ability endowment (since it is likely correlated with the mother's ability endowment). But, setting that problem aside, note that the standard error on "proportion of

[18] In particular, a one-standard deviation in child care quality causes a .04 to .08 standard-deviation increment in child cognitive ability. Quality is assessed using the Observational Record of the Caregiver Environment (ORCE).
[19] Estimation of a first-differenced version of the value-added specification would eliminate the fixed effects, but Blau (1999) points out this is difficult or impossible due to limitations of existing data, as it requires three outcome observations and two lagged input observations. Even if feasible, this approach would entail a severe efficiency loss.
[20] According to footnote 7 of their paper, this is the only variable in the prediction equation for maternal employment that does not also appear in the child outcome equation.

weeks worked by the mother" increases from 1.864 to 26.831 when this instrument is used in place of running OLS (see columns 1 and 2 of their Table 2). The latter figure implies that, to attain significance at the 5% level, the coefficient would need to be roughly -53, implying that a mother shifting from no work to full-time work in the 2nd through 4th years lowers the PPVT test score by 53 points (the mean and standard deviation of the score are 91.2 and 18.1 respectively).

James-Burdumy (2005) uses percent of the county labor force employed in services to instrument for maternal employment in her sibling fixed effects specification. Comparing columns FE and IV-FE from her Table 3, the standard error on the variable for "average hours worked per year in the first 3 years of the child's life" increases from .00178 to .01205, a factor of 7. Given the IV-FE standard error, the coefficient on maternal employment would have to be roughly -.024 to attain significance at the 5% level. This means that increasing average hours from 0 to 2000 over the first three years would lower the PPVT test score by 48 points.

Clearly, in both these papers, the instruments are too weak for IV estimators to identify plausibly sized effects of maternal employment on child outcomes. The main advantage of our approach is that the welfare policy and local demand instruments that we employ are much stronger. Indeed, in Bernal and Keane (2006), where we implement 2SLS, we note that the first stage marginal R^2 values obtained using these instruments are quite large relative to what one typically sees in the IV literature (i.e., about .075 to .09), and, in the second stage, standard errors on maternal employment and day care use do not "explode" when these instruments are used.

Finally, Bernal (2005) estimates a structural model of work and child care decisions by married women after childbirth. Estimation of the child's cognitive ability production <u>jointly</u> with the mother's work and child care decision rules implements a selection correction, adjusting for the fact that certain types of children are more likely to be put in child care and/or to have working mothers. Her results suggest that an additional year of full-time work and child care use reduces child cognitive ability test scores by about 2% (for children ages 3 through 7).

As we noted earlier, Bernal (2005) relies on exclusion restrictions that are controversial. Specifically, she assumes movement along the mother's and father's age-wage profile generates exogenous variation in their wage rates, which in turn affects the mother's work and child care decisions, but does not directly affect child outcomes. We believe that additional, and stronger, instruments are available for single mothers, based on welfare rules and local demand conditions.

3. Construction of Instruments using Welfare Rules and other Policy Variables

To deal with the selection problem that arises because children placed in child care may differ systematically from children who are not, we propose to use welfare policy rules as instruments (or exclusion restrictions) to help identify our selection model. Welfare rules are known to have a large impact on labor supply of single mothers (see, e.g., Moffitt (1992)). To construct our instruments, we collect detailed information on State welfare policies from many sources. The working paper version contains a detailed list of sources, and a detailed discussion of the construction of the instruments. Here, we only briefly highlight the key aspects of Section 1115 welfare waivers and the 1996 Welfare Reform (PWRORA) that are relevant to this work. Table 1 presents the complete instrument list, including all the policy variables. Each instrument has up to three subscripts: *i* for individual, *s* for State and *t* for period (quarter in our case).

3.1. Benefit Termination Time Limits

Under AFDC, single mothers with children under 18 were *entitled* to receive benefits, as long as they met the income and asset eligibility requirements. But under the Section 1115 Waivers, and under TANF, the States could set time limits on benefit receipt. Indeed, PWRORA forbids States from using federal funds to provide benefits to adults beyond a 60-month lifetime time limit, and it allows states to set shorter time limits. For instance, California imposes a 5-year time limit, and Texas and Florida impose termination time limits in the 2-3 year range.

Time limits can have both direct indirect effects. The direct effect is straightforward (i.e., when the woman hits the time limit she becomes ineligible). The indirect effect refers to the more subtle idea that if individuals are forward-looking they will try to “save” or “bank” months of eligibility for later use. In this paper, a total of <u>five</u> variables that capture both effects of time limits are included in the instrument list. These incorporate both time limits created under TANF and earlier under AFDC waivers, and are listed in Table 1. We include, for example, a dummy for whether a single mother’s State of residence had imposed a time limit (TLI_{st}) in time t, a dummy for whether the time limit could possibly be binding (TL_HIT_{ist}), and the woman’s maximum potential remaining time before hitting the time limit ($REMAIN\_TL\_ELIG_{\text{ist}}$).

It is worth emphasizing that we go to a great deal of effort to construct instruments that are person specific. For example, consider TL_HIT_{ist}. Let’s suppose a woman resides in a State that had imposed a 5-year time limit 6 years earlier. Then it is possible that she could have hit the limit, provided her oldest child was at least 5. If her oldest child was less than 5, she could not have participated in AFDC/TANF for 5 years, and therefore could not have hit the limit. Thus, using information on age of the oldest child, we can tailor the instrument to individual cases.

Crucially, we do not use a woman's actual welfare participation history to determine her remaining quarters of eligibility, as the actual participation history is endogenous. Our assumption is that the welfare policy rules, as well as demographics like ages and numbers of children, are exogenous (conditional on controls for mother characteristics). Thus, all our individual specific instruments are functions of policy parameters and demographics alone.

3.2. Work Requirement Time Limits and Work Requirement Exemptions

Work requirements increase the time/utility cost of receiving welfare benefits. Under TANF, recipients must participate in "work activities" within two years of coming on assistance in order to keep receiving benefits. But many States have adopted shorter work requirement time limit clocks. Due to variation in when States implemented their TANF plans, and in the length of their work requirement clocks, there is substantial variation across States in how early single mothers could have been subject to binding work requirements. Also, States have the option to exempt single parents with children up to 1 year of age from work requirements and have the flexibility to provide exemptions to other families. Thus, within a State, there is variation across women in whether work requirements can be binding, based on age of the youngest child.

We construct a total of five variables, listed in Table 1, to capture these various effects. For example, WR_HIT_{ist}, is an indicator for whether the woman could have been subject to work requirements (based on her age, length of the work requirement, time since the requirement had been implemented, age of her oldest and youngest child, etc.), and $AGE\_CHILD\_EXEM_{st}$ is age level for the age of youngest child exemption in place in State s at time t.

3.3. AFDC/TANF Benefit Levels, Earnings Disregards and Benefit Reduction Rates

AFDC/TANF benefits are, roughly speaking, determined by a formula in which a State specific grant level, which is an increasing function of number of children under 18, is reduced by some percentage of the recipient's income. One variable we use to characterize the system is the maximum *potential* real monthly AFDC/TANF benefit amount (BEN_{ist}), assuming zero earnings, constructed using the State payment standard for the corresponding family size of the single mother. We put this variable in real terms using a region-specific CPI.[21]

[21] The BLS computes the CPI for 24 metropolitan areas and for four regions (west, south, midwest and northeast).

Under AFDC, benefits were reduced as income increased according to a "benefit reduction rate" (BRR) that changed several times over the history of the program. Under waivers and TANF, the BRR was made State specific, and it now varies considerably across States.

In addition, AFDC used "earnings disregards" to encourage work among participants. That is, if a recipient started working, then for a period of time, a fraction of her earnings would not be subject to the BRR. Generally, the disregard consisted of a "flat" component (e.g., the first $30 of monthly earnings) and a "percentage" part (e.g., one-third of earnings beyond the flat part). Both would be eliminated after a certain number of months of work.

Starting in late 1992, many states obtained waivers to increase the income disregard. Under PRWORA, States are not required to adopt any particular earned income disregards, so a great deal of State heterogeneity has emerged. A few States expanded disregards and allowed them to apply indefinitely. We code the BRR and the percentage disregard together in the variable $PERC\_DISREGARD_{st}$. Flat disregards are coded in $FLAT\_DISREGARD_{st}$.

3.4. Child Support Enforcement

Child support is an important source of income for single mothers, despite widespread non-payment by non-custodial fathers.[22] The Child Support Enforcement (CSE) program, enacted in 1975, has implemented programs to locate absent parents and establish paternity. CSE expenditures have significantly increased from $2.9 billion in 1996 to $5.1 billion in 2002 (a 76% increase). These expenditures are an important indication of how likely a single woman is to collect child support. We include a measure of State level CSE activity by taking the State CSE expenditure and dividing it by the State population of single mothers ($ENFORCE_{st}$).

3.5. Child Care Subsidies and the Child Care and Development Fund (CCDF)

The CCDF is a block grant to states to provide subsidized child care programs for low-income families, including those who are not current or former welfare recipients. Under the CCDF, states have autonomy to design child care assistance programs for low-income families, and a great deal of heterogeneity has emerged in State program design. As an additional policy instrument, we use the State CCDF expenditure per single mother ($CCDF_{st}$). This variable measures the availability and generosity of child care subsidies in a State.[23]

[22] In 2002, child support accounted for approximately 6.5% of single mother's real incomes (March CPS).
[23] We could instead use State program parameters, such as monthly income eligibility criteria, reimbursement rate ceilings or co-pay rates. We opt not to use these measures due to problems associated with rationing.

3.6. Other Instruments: Earned Income Tax Credit (EITC) and Local Demand Conditions

The EITC, enacted in 1975, is a refundable Federal income tax credit that supplements wages for low-income families. Major expansions of the federal EITC occurred in 1986, 1991, 1994 and 1996. Due to these expansions, the number of families receiving EITC increased from 6.2 million in 1975 to 19.5 million in 2000.[24] After the expansions in the mid-1990s, the EITC became a sizable wage subsidy to low-income families. Thus, it may provide an important work incentive.[25] To account for this effect we construct the EITC phase-in rate ($EITC_{ist}$) using Federal and State level EITC rules together with the mother's family composition.

Finally, we use three variables that measure local demand conditions as instruments: the State unemployment rate at time *t*, the 20th percentile wage rate in the woman's State of residence at time *t*, and the percent of the State labor force employed in services at time *t*.

4. The Model

We first present a structural model of single mother's decisions about work and day care use, and how these affect child cognitive outcomes. Rather than presenting a *general* model, we describe in detail a *specific* model we might actually estimate, given available data and computational limitations. This helps clarify the types of assumptions that are necessary to solve and estimate such a model. Next, we describe a "quasi-structural" approximation to the structural model. This helps clarify how certain assumptions needed for full structural estimation can be sidestepped if one only estimates an approximation. However, as we noted earlier, this does not mean that implicit assumptions in these areas will not still influence the interpretation of results.

4.1. Overview of the Structural Model

Consider a woman who makes sequential choices about work, child-care and welfare participation in each period *t* following the birth of a child and until the child goes to primary school at age 5. For expositional convenience we consider a woman with a single child, and ignore additional fertility decisions (although we allow for multiple children in the empirical work). In our model the time periods correspond to 3-month intervals. We allow for three work options (full-time, part-time or no work), while the child care and welfare choices are binary. As the option of working (either full-time or part-time) and not using child care is not feasible, there

[24] U.S. House of Representatives Green Book 2000, p. 813.
[25] E.g., in 2003, the phase-in rate for a family with one child was 34%, and 17 States supplement the federal credit.

are at most 8 alternatives in a woman's choice set. Of course, depending on the woman's state of residence and duration of welfare participation, this choice set will vary (e.g., a woman who resides in a State with a 36 month welfare time limit won't have the option to receive welfare beyond 36 months, reducing her choice set). Formally, we denote the choice set as:

$$J_{st} = \{(h_t, g_t, I_t^c) : h_t = 0,1,2,\ g_t = 0,1,\ I_t^c = 0,1\}$$

where h_t denotes hours of work (2=full-time, 1=part-time, 0=no work), g_t is an indicator for welfare participation, and I_t^c is an indicator for utilization of child care in period t. The choice set J_{st} has both State (s) and time (t) subscripts due to variation in the welfare rules (e.g., a woman's duration of welfare receipt may make her eligible for welfare in one State and not another).

It will also be useful to define the choice indicator:

$$d_t^j = I[\text{alternative } j \in J_{st} \text{ is chosen in period } t]$$

Next, we need to specify the current-period utility function given choice of option j. Following Bernal (2005), a reasonable functional form would be:

$$\begin{aligned} U_t^j = {} & (1/\alpha_1)c_t^{\alpha_1} + \alpha_2 h_t + \alpha_3\left(\frac{A_t^\lambda - 1}{\lambda}\right) + \alpha_4 g_t + \alpha_5 I_t^c + \alpha_6 I_t^c (1 - I[\textstyle\sum_{\tau=1}^{t-1} I_\tau^c > 0]) \\ & + \alpha_7 I[t=1] I_t^c + \alpha_8 I[t<5] I_t^c + \alpha_9 I_{t-1}^c I_t^c + \varepsilon_t^j \qquad for\ \ j \in J_{st} \end{aligned} \tag{2}$$

where the consumption c_t is given by the budget constraint:

$$c_t = w_t.h_t.(250) + N_t + g_t.B(w_t, h_t, g_t, D_t, R_{st}) - cc(w_t, h_t, N_t, D_t, \theta_{st}).I_t^c \tag{3}$$

The utility function in (2) has a CRRA form in consumption, with parameter α_1. The parameter α_2 is the disutility from work. A_t is cognitive ability of the child, which is generated by a production function we define below. The mother gets utility from the child's cognitive ability according to a CRRA function with parameter λ, as in Bernal (2005). She estimated $\lambda<1$, implying mothers get diminishing marginal utility from child ability, and therefore have an incentive to engage in behaviors to compensate children with relatively low ability endowments.

The parameter α_4 is the disutility (or "stigma") from welfare participation. As was noted by Moffitt (1983), such a term is necessary to capture the pervasive feature of the data that many women who are eligible for welfare benefits based on their income do not collect them.

The α_5 through α_9 terms in (2) capture various aspects of the utility/disutility from child-care use. These terms are patterned after those in Bernal (2005), who found they are all necessary to fit data on child care utilization well.[26] The parameter α_5 is a general non-pecuniary benefit/cost associated with the use of child-care. α_6 is an extra cost of initiating child-care if one hasn't used it before. This may capture the search time cost of finding a daycare center, and/or the psychic cost of first time separation from the child. The parameter α_7 is an extra cost from using child-care during the first quarter after birth (t=1), and α_8 is an extra cost from using child-care before the child is one year old (t<5). Both of these parameters capture the fact that it is more difficult to find day care centers that will take infants, and that infant care is generally more expensive, along with the fact that the psychic cost of separation from the child is greater when the child is very young. α_9 captures the fact that utility/disutility of child care use may depend on whether child care was used in the immediately preceding period.

Finally, ε_t^j is an alternative-specific random taste shock. FIML estimation would require a distributional assumption on these stochastic terms.[27] For example, we could assume they are multivariate normal and independent over time. Since some alternatives are more similar than others, it would also be necessary to allow the ε_t^j to be correlated across alternatives.

Turning to the budget constraint (3), earned income is given by $w_t \cdot h_t \cdot (250)$ because we define part-time work (for a quarter) as 250 hours, and full-time as 500 hours. This grouping of hours facilitates estimation, since it keeps the choice set purely discrete. Keane and Moffitt (1998) adopted this approach to jointly model labor supply and welfare participation. They argued that grouping was desirable because hours are very concentrated at 20 and 40 per week, and because much of the variation away from those figures is likely to be measurement error. They also found their results were not sensitive to how hours are grouped. The next term in the budget constraint, N_t, denotes non-labor income. This may include child support payments.

The third term in the budget constraint is $B(w_t, h_t, N_t, D_t, R_{st})$, the welfare benefit rule, which determines the benefit that the woman receives if she chooses to participate in welfare (i.e., if g_t=1). This depends on the wage rate w_t, hours of work h_t, non-labor income N_t, the duration of pervious welfare participation D_t, and a vector of state and time specific welfare

[26] The exception being the interaction between current and lagged child care, which she did not need to include.
[27] Note that a distributional assumption is necessary not only to form the likelihood function, but also to solve the agent's dynamic optimization problem.

benefit rules parameters R_{st}.[28] One such parameter is the grant level that a woman with no income receives. This differed greatly across States and over time even under AFDC. Under TANF and waivers, there has also emerged a great deal of heterogeneity across States in the rate at which welfare benefits are reduced if a woman has earned or unearned income. The duration of prior welfare participation matters for benefits because some states eliminate or reduce the benefit by some proportion when a critical level of duration is reached (e.g., in California the benefit is reduced, but not eliminated, after 5 years). Such features are captured in R_{st}.

The final term in the budget constraint includes $cc(w_t, h_t, N_t, g_t, \theta_{st})$, the cost of child care. Under CCDF funded State child-care subsidy programs, required co-pays for day care depend on earned and unearned income. In many States, TANF participants (g_t=1) are not required to make co-pays. The vector θ_{st} captures how co-pay and eligibility requirements vary across States.

Aside from the budget constraint, a woman faces two other constraints that influence her work and child-care utilization decisions: her wage function and the child cognitive ability production function. In order to explain these, it is useful to first define w_o as the "initial wage" of the woman, prior to giving birth. This is the observed wage for an employed woman, or a latent offer wage based on latent earnings capacity for a non-working woman. We model the initial wage as a function of observed and unobserved characteristics of the woman as follows:

$$ln\, w_o(\mu_w) = \mu_w + \theta_1 educ + \theta_2 age + \theta_3 age^2 + \theta_4 race + \theta_5 AFQT + \overline{\theta}_6 \tau_{s,o} + v_{wo}$$

Here, the intercept μ_w represents *unobserved* heterogeneity in the mother's skill endowment. The variables education (*educ*), *race* (a dummy equal to 1 if the child is non-white), and the *AFQT* score capture *observed* heterogeneity in the skill endowment, while *age* (the woman's age at the time of child birth) captures movement along the life-cycle wage path. The vector $\tau_{s,o}$ is a set of local demand conditions in woman's State of residence at the time of the initial wage observation,[29] and $\overline{\theta}_6$ is a vector of parameters associated with $\tau_{s,o}$. Finally, v_{w0} captures transitory shocks to income and/or measurement error, which we assume are serially independent. FIML would require a distributional assumption on v_{w0}, such as $v_{w0} \sim N(0, \sigma_w^2)$.

[28] Recall that in writing the model we are assuming, for simplicity, that the woman has only one child. But, in reality, welfare benefits also depend on the number of children, a fact that we will account for later.

[29] In particular, we will use the unemployment rate, the average wage at the 20th percentile of the wage distribution and the fraction of employment in the services sector.

It will be useful to define $\ln w_0(\mu_w) = \ln \overline{w}_0(\mu_w) + v_{w0}$, so that $\ln \overline{w}_0(\mu_w)$ represents the persistent part of the woman's log offer wage at the time of childbirth. Then, after childbirth, the wage a woman can earn upon returning to work is given by the following process:

$$ln\, w_t(\mu_w) = ln\, \overline{w}_0(\mu_w) - \delta \cdot t + \phi_1 E_t + \phi_2 f_{t-1} + \phi_3 p_{t-1} + \phi_4(E_t \cdot educ) + \overline{\theta}_6 \tau_{st} + v_{wt} \quad (4)$$

Here, δ is the depreciation rate of human capital, so that $\delta \cdot t$ captures the percentage depreciation of a woman's offer wage if she leaves the labor force for t periods after childbirth. Acquiring work experience can counteract this depreciation. $E_t = \sum_{\tau=0}^{t-1} h_t$ is total work experience since birth, f_{t-1} and p_{t-1} indicate whether the woman worked full-time or part-time during the immediately preceding period, and $E_t \cdot educ$ is an interaction between experience and education. The vector τ_{st} is the set of local demand conditions in the woman's State of residence in period t after childbirth, and $\overline{\theta}_6$ is the vector of parameters associated with τ_{st}. Finally, v_{wt} is a stochastic term due to transitory shocks to productivity and/or measurement error. Again, for FIML, we would need a distributional assumption on v_{wt} in order to solve the dynamic optimization problem and form the likelihood function (e.g., $v_{wt} \sim N(0, \sigma_w^2)$).

Next, we describe the child cognitive ability production function. We assume that a child is born with a cognitive ability endowment, A_o. We assume the endowment is correlated with a set of observable variables, and also contains an unobservable component, as follows:

$$\begin{aligned} \ln A_o(\mu_s) = (\rho\mu_w + \mu_k) + \gamma_1 AFQT + \gamma_2 educ + \gamma_3 race + \gamma_4 age + \gamma_5 age^2 \\ + \gamma_6 I[age < 20] + \gamma_7 I[age > 33] + \gamma_8 EXPBEF + \gamma_9 I[worked\ bef] \quad (5) \\ + \gamma_{10} gender + \gamma_{11} BW \end{aligned}$$

Here, the intercept $\mu_s \equiv (\rho\mu_w + \mu_k)$ represents unobserved heterogeneity in the child's cognitive ability endowment. It consists of a part $\rho\mu_w$ that is correlated with the unobserved part of the mother's skill endowment, and a part μ_k that is not. There is also a part of the child ability endowment that is correlated with a set of observed characteristics of the mother: her AFQT score (*AFQT*), education (*educ*), *race*, age at the time of childbirth (*age*), work experience before giving birth (*EXPBEF*), and an indicator for whether she worked in the year prior to giving birth (*I*[*worked bef*]). Finally, there is a part of the endowment that is correlated with observed characteristics of the child, although the only such observables we have are birthweight (*BW*) and *gender*, a dummy variable indicating if the child is female.

Note that we control for mother's age at birth in a very flexible way by including *age*, age^2 and indicators for whether she was under 20 or over 33 ($I[age<20]$ and $I[age>33]$). We do this because there is some evidence that children of teenage mothers (and older mothers) are less healthy and/or have worse cognitive test scores. However, there is also evidence that this association vanishes if one controls for mother's characteristics like education and income.[30] Indeed, we find below that age is completely insignificant in the production function.[31]

We emphasize that the coefficients γ_1 through γ_{11} in (5) do not capture causal effects, but merely *correlation* between observables and the child's cognitive ability endowment. It is desirable to let observables "sop up" as much of the child's unobserved ability endowment as possible, as this should reduce the sensitivity of our results to the distributional assumptions we place on the unobserved heterogeneity terms. Indeed, if we could perfectly control for the skill endowment using observed correlates, the selection problem in estimating the impact of maternal time on child outcomes would vanish. This logic applies to any method used to estimate the effect of maternal time, whether it be single equation IV, quasi-structural estimation, or FIML.

Finally, we turn to the cognitive ability production function itself. This captures the notion that the child's initial cognitive ability endowment, A_o, interacts with subsequent inputs – maternal time (T), child care (C) and goods (G) – to determine the child's cognitive ability at age t, denoted A_t. We start with a specific version of equation (1), in which A_o enters explicitly, and in which only cumulative inputs matter.[32] Dropping the mother and child subscripts, we write:

$$\ln A_t(\mu_s) = \ln A_o(\mu_s) + \gamma_{11}T_t + \gamma_{12}C_t + \gamma_{13}\ln G_t \qquad (6)$$

Here, T_t denotes the cumulative input of maternal time through age t, C_t denotes the cumulative input of alternative care givers' time, and G_t denotes the cumulative input of goods. It is

[30] See, for example, Lopez (2003), Geronimus et al (1994) and Bernal and Keane (2006).
[31] If age mattered in the production function, it would call into question the validity of our TANF and waiver related welfare policy instruments. These policy rules are correlated with mother's age at childbirth, because the teenage mothers in the NLSY79 cohort had children at too early a date to be affected by TANF or waivers.
[32] A completely general functional form, where inputs at age t may have different effects on ability at each age t', and the ability endowment μ_s may have different effects on ability at each age, is infeasible due to proliferation of parameters. We adopt the simplification, familiar from the human capital literature, that: (i) only cumulative inputs matter, rather than their timing, and (ii) the effect of the permanent unobservable is constant over time. Similarly, in the standard Mincer earnings function, only cumulative education and experience are assumed to affect human capital, and the unobserved skill endowment is typically assumed to have a constant effect on log earnings.

convenient to let goods enter in log form, for reasons that will become clear shortly. Note that, comparing (1) with (6), The term $\alpha_4 X_t + \mu + \delta$ (i.e., the observed and unobserved parts of the ability endowment) has been subsumed in ln $A_o(\mu_s)$. And we drop ε in (1) because the dependent variable in (6) is the actual ability rather than a noisy test score measurement. In (6) we assume homogeneous coefficients on the time and goods inputs. This is expositionally convenient for the remainder of this section, but we will allow for heterogeneous coefficients in Section 4.2.

Now, as T and G are not directly observed, we must make further assumptions that relate them to observables in order to obtain an estimable equation. Consider first the measurement of the maternal time input. One could imagine a model where mothers decide how much “quality” time to devote to the child while at home (e.g., children’s time is divided between day-care, “quality” time with the mother, and time spent watching TV while the mother does housework). But, since we don’t observe actual contact time between mothers and children (let alone the subset that is “quality” time),[33] we simply side-step the issue by assuming that $T_{it} = T\text{-}C_{it}$, where T is total time in a period. Thus, we distinguish between only two types of time (i.e., time with the mother and time in child-care). This means we can rewrite (6) as:

$$\ln A_t(\mu_s) = \ln A_o(\mu_s) + (\gamma_{11}T)\cdot t + (\gamma_{12} - \gamma_{11})C_t + \gamma_{13}\ln G_t \tag{7}$$

Equation (7) clarifies that we can only really estimate $\gamma_{12} - \gamma_{11}$, the effect of time in child-care *relative* to the effect of mother’s time.

Next, consider the fact that goods inputs G are, to a great extent, unobserved. For example, the NLSY contains information on books in the home, but lacks other potentially important goods inputs like nutrition, health care, tutors, etc.. To deal with this, consider a specification where the decision rule for cumulative monetary investment (in the form of goods) in child ability (conditional on work, income and child-care usage decisions) is given by:

$$\ln G_{it} = \pi_0 + \pi_1 X_i + \pi_2 \mu_{s_i} + \pi_3 C_{it} + \pi_4 \ln I_{it}(W, H; R_{ist}) + \pi_5 t + \varepsilon_{it}^g \,. \tag{8}$$

This is a conditional decision rule (or demand), obtained as the second stage in an optimization process, where, in the first stage, a mother chooses the child-care time inputs C and hours of market work H. The notation $I_{it}(W, H; R_{ist})$ highlights the dependence of income on

[33] As we discussed in section 2, the NLSY’s “HOME” environment index is based on such variables as how often the child is read to, eats meals with the parents, or talks with the mother while she does housework. But it is no possible to use these variables construct a single measure of the <u>total</u> maternal quality time input.

wages, hours of market work, and welfare rules R_{st} that govern how benefits depend on income. Equation (8) can be viewed as a simple linear approximation to the more complex decision rule generated by the dynamic model. It captures the notions that: (i) a mother's decisions about goods inputs into child development may be influenced by (i.e., made jointly with) her decisions about work hours and child care, and (ii) per-period inputs depend on a mother's characteristics *X,* such as education (which determine human capital), and a child's ability endowment μ_{s_i}. The time trend in (8) captures growth of cumulative inputs over time. The stochastic term, ε_{it}^{g}, captures a mother's idiosyncratic tastes for investment in the form of goods.[34]

Now, substituting (8) and (5) into (7), we obtain:

$$\begin{aligned}
\ln A_t(\mu_s) &= \ln A_o(\mu_s) + (\gamma_{11}T)\cdot t + (\gamma_{12} - \gamma_{11})C_t \\
&\quad + \gamma_{13}[\pi_0 + \pi_1 X_i + \pi_2 \mu_{s_i} + \pi_3 C_{it} + \pi_4 \ln I_{it} + \pi_5 t + \varepsilon_{it}^{g}] \\
&= \gamma_{13}\pi_0 + (\gamma_{11}T + \gamma_{13}\pi_5)\cdot t + (\gamma_{12} - \gamma_{11} + \gamma_{13}\pi_3)C_t \\
&\quad + \gamma_{13}\pi_4 \ln I_t + X(\gamma + \gamma_{13}\pi_1) + (1 + \gamma_{13}\pi_2)\mu_s + \gamma_{13}\varepsilon^{g} \\
&= \beta_0 + \beta_1 \cdot t + \beta_2 C_t + \beta_3 \ln I_t + X\beta_4 + \hat{\mu}_s + \hat{\varepsilon}^{g}
\end{aligned} \tag{9}$$

Equation (9) is estimable, because all the independent variables are observable. However, we must be careful about the appropriate estimation method and interpretation of the estimates. As we have stressed, child care utilization C_t may be correlated with the unobserved part of the child's ability endowment μ_s. It may also be correlated with ε^g, the unobserved taste shifter in equation (8). This problem arises if tastes for child care use are correlated with tastes for goods investment in children, as seems plausible.[35] Thus, for welfare rule parameters R_{st} and local demand conditions τ_{st} to be valid instruments for estimating (9), they must be uncorrelated with both of these error components, which we view as a plausible exogeneity assumption.[36]

The cumulative income variable in (9) is also potentially endogenous, for multiple reasons. First, income depends on the jointly made child care use and work decisions. Hence it is potentially correlated with child ability for the same reasons as are operative for child care usage.

[34] This may arise due to heterogeneous preferences for child quality.
[35] For instance, a mother with a high taste for child quality may both spend more time with the child (i.e., use less day care) and invest more in the child in the form of goods. This would tend to bias estimated effects of day care in a negative direction, since not only the maternal time input but also the goods input is lower for children in day care.
[36] To our knowledge, it has not been previously noted that consistent estimation of an equation like (9) requires instruments that are uncorrelated with <u>both</u> the unobserved part of the child's skill endowment, μ_s, and the mother's tastes for goods investment in the child, ε^g.

Second, income depends on the mother's wage rate, which depends on her unobserved ability endowment. To the extent that this is correlated with the child ability endowment (i.e., $\rho \neq 0$ in (5)), this will also generate correlation between income and μ_s. Thus, we need to instrument for mother's income as well. Again, we will argue that the welfare rules R_{st} and local demand conditions τ_{st} provide plausibly valid instruments, since they should have important effects on work decisions, yet it is plausible that they are uncorrelated with child ability endowments.

Assuming our quasi-structural approach, using welfare rules and local demand conditions as exclusion restrictions, provides consistent estimates of (9), it is important to recognize that the child care "effect" we estimate is $\beta_2 = \gamma_{12} - \gamma_{11} + \gamma_{13} \cdot \pi_3$. This is the effect of child care time (γ_{12}) *relative* to mother's time (γ_{11}), plus the effect of any change in goods inputs that the mother chooses because of using day care ($\gamma_{13} \cdot \pi_3$). In light of this, it is important to understand the limitations of estimates of (9). For instance, such estimates cannot predict how a policy like a child care subsidy would affect child outcomes. Such subsidies would not only alter day care use, but possibly also the budget constraint conditional on I_{it}, and I_{it}^c, and hence the decision rule for goods inputs (8). Thus, it may alter goods inputs in a way not captured by $\gamma_{13} \cdot \pi_3$. The problem arises because, while γ_{11}, γ_{12}, and γ_{13} are structural parameters of the production technology, the reduced form parameter π_3 in the decision rule for goods is not policy invariant.

Thus, in interpreting our estimated effects of child care on child cognitive outcomes, one must be careful to view them as applying only to policies that do not alter the decision rule for goods in investment in children (8). As this decision rule is conditional on work, income and child-care decisions, it will be invariant to policies that leave the budget constraint conditional on those decisions unchanged. A work requirement that induces a woman to work and use child care, but that leaves her wage rate and the cost of care unaffected, would fall into this category.

We have used a very simple form for (9) to clarify estimation issues, but we will adopt more general production functions in our empirical work. For instance, we include interactions between the child's initial (latent) ability and household inputs, to allow the effect of inputs to vary depending on the type of the child.[37] Bernal (2005) found that returns to maternal time in production of child cognitive ability are greater for children with higher initial skill endowments.

[37] As the child's initial ability endowment is partly determined by the genetic endowment, these interactions capture the notion that genetic endowments interact with environment influences (inputs) to determine cognitive outcomes.

Of course, we do not observe actual cognitive ability of children, but instead a set of cognitive ability test scores from which we infer it. Let S_t denote the (age adjusted) test score and let the measurement error model be specified as:

$$ln\, S_t = ln\, A_t(\mu_s) + \eta_1 d_{1t} + \eta_2 d_{2t} + v_{st} \tag{10}$$

where d_{1t} and d_{2t} are test dummies (i.e., PIAT or PPVT) to capture mean differences across the tests (see Section 5). The term v_{st} is measurement error, and we assume $v_{st} \sim N(0, \sigma_v^2)$.[38]

In describing the structural model, we have ignored fertility, and assumed a mother has just one child. In a model with multiple children, one would need to specify how total maternal contact time is allocated among children, and take a stand on the extent to which maternal time is a "public good" (i.e., do children get the same benefit from maternal time regardless of how many children are present?). Thus, structurally modeling of families with multiple children is difficult. In either a single equation IV or quasi-structural approach, we can sidestep these issues by including the number of children in the score equation, as well as interacting it with the other inputs. Effects of inputs may plausibly vary with number of children, e.g., when a mother works and puts children in day care, the reduction in contact time may be less if she has multiple children (since time with each child was less to begin with) than if there is only one child.

A key issue to be addressed in structural estimation is what mother's know, because this importantly affects they solve their dynamic optimization problem. For instance, in a similar model, Bernal (2005) assumes that mother's know the cognitive ability endowment μ_s of their child, but that it is unobserved by the econometrician. While the assumption that mothers know more than econometricians is reasonable, the assumption that they have complete information may be extreme. Hence one might want to consider alternative formulations where μ_s is split up into a component the mother observes and a component she does not observe. Again, explicit assumptions on this issue can be avoided in IV or quasi-structural estimation, but proper estimation methods and interpretation of results will depend on ones implicit assumptions.[39]

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[38] A distributional assumption is needed for FIML or quasi-structural estimation, but can be avoided in IV or MOM.

[39] For example, OLS and sibling fixed effects estimators implicitly assume that mothers do not know the cognitive ability endowments of their children. If mothers do know μ_s, it creates an important potential source of bias in such estimates of the cognitive ability production function. For instance, if mothers compensate low endowment children by spending more time with them (and using day care less), this will upward bias OLS estimates of the effect of day care on cognitive development. This problem cannot be dealt with by use of sibling fixed effects estimators, because, if mothers can see the endowment differences across their children, they may treat them differently.

Structural estimation would also require assumptions regarding what mothers know about the cognitive ability production function, the wage equation, and the welfare rules. If mothers understand each of these, then there are three key sources of dynamics in the model. Mothers know: (i) how their decisions about working after childbirth affect the evolution of their human capital, according to equation (4), (ii) how their decisions about work and child care affect cognitive ability outcomes for their child (as determined by equation (9)), and (iii) how welfare participation decisions affect future welfare eligibility, future choice sets and future budget constraints (when there are termination, work requirement and/or benefit reduction time limits).

Again, non-structural approaches would make implicit assumptions in these areas. For instance, a child fixed effects estimator implicitly assumes that mothers are not learning about child ability itself, or the form of the cognitive ability production function, as test scores are realized. If they were, the shock to the time *t* test score would affect inputs between time *t* and time *t*+1.[40] Thus, the strict exogeneity assumption of the fixed effects estimator is violated.

Finally, structural estimation would typically involve further assumptions about where unobserved heterogeneity enters the model. We have already specified that there is unobserved heterogeneity in mother and child ability endowments (μ_w and μ_s respectively). Typically, additional heterogeneity is required in order to fit the data. For instance, a typical specification would allow mothers to be heterogeneous in their tastes for work (α_2), tastes for welfare participation (α_4), and tastes for child care utilization (α_5).

Solution of the mother's optimization problem would require us to solve numerically for the value function at each point in the state space. Define Ω_t as the state at period *t* that arises as a result of the decisions made up to *t*. The simplest version of our model is characterized by five state variables that evolve endogenously: quarters of work experience since childbirth (E_t), the work and child care decisions during the immediately preceding period (h_{t-1}, I_{t-1}^c), cumulative quarters of child care use (C_t), and cumulative quarters of welfare participation (D_t). Thus, we have $\Omega_t = \{E_t, h_{t-1}, C_t, D_t, I_{t-1}^c\}$. Note that the state variables are all incremented in the obvious way at each age *t* based on the work, day care use and welfare participation decisions at *t*-1.

[40] This is true if work/day care choices depend on perceived child ability. For instance, suppose mothers compensate low ability children by spending more time with them. Then a negative shock to the test score at time *t* (which is part signal and part noise) would cause an increase in maternal time (i.e., reduction in work and day care) between *t* and *t*+1. Using fixed effects or first-difference estimators, this induces a negative bias in estimates of effects of maternal time on child outcomes (i.e., from *t* to *t*+1 the test score will tend to rise, while maternal work and day care use fall).

In addition, each woman has a set of individual specific state variables that stay fixed over time, or that evolve exogenously. These are: (i) her child's cognitive ability endowment, gender, and birthweight, and (ii) her skill endowment, age, education, race, AFQT score, whether and how much she worked prior to childbirth, and number of children, and (iii) her State specific welfare policy rules, child care subsidy parameters and local labor demand conditions. As result of these variables, each woman faces her own unique optimization problem.[41]

A final issue is that the choice problem changes fundamentally when a child reaches roughly age 5, and he/she begins kindergarten. Then day care is no longer relevant (although after school care is still an issue). One strategy is to avoid modeling decisions beyond the time horizon of interest by specifying a terminal value function.[42] Then, FIML estimation of the structural model requires that, at any given trial parameter vector, we solve an agent's dynamic programming (DP) problem numerically by "backsolving" from the terminal period T to t=1. Then, we can form the joint probabilities of observed choices, wages and test scores conditional on observed states, and form the likelihood function. Both the DP solution and the likelihood evaluation would be extremely computationally burdensome in this case.

4.2. A Quasi-Structural Approach: Approximate Solution of the Structural Model

An alternative way to estimate the effect of mother's employment and child care decisions on child cognitive ability is to form approximations to the decision rules for work and day care implied by the structural model, and to estimate these jointly with a cognitive ability production function and a wage equation. We now describe this "quasi-structural" approach.

The decision rules for work and day care should, in theory, be functions of all the state variables in our structural model. There is no basis for excluding any variables from these decision rules. For instance, any variable that affects wages, or child ability, must affect both work and day care decisions in our model. Similarly, any variable that affects childcare decisions will affect work decisions, and *vice versa*. In contrast, the cognitive ability production function (9) and the wage equation (4) only depend on a subset of the state variables. Thus, our theoretical framework delivers exclusion restrictions to identify the selection model.

[41] Still, we typically write one woman's optimization problem only in terms of endogenous state variables Σ_t.
[42] For instance, Bernal (2005) models a mother's decisions from t=1, the first quarter after childbirth, until t=20. At T=21, she assumes a terminal value function that is a flexible function of the state variables. In the present case, we could write $V_T(\Sigma_T)=P(A_T, E_T, D_T)$ where $P(\cdot)$ denotes a flexible polynomial function. In this terminal value function, the woman cares about the cognitive ability of her child, her own work experience (which will affect her future earning capacity) and her accumulated welfare usage at time T=21 (which affects her eligibility for future benefits).

Consider first the work decision rule implied by our structural model. We approximate it as a multinomial probit, with full-time, part-time and no work as the three alternatives, where we approximate the value function V_f^* for full-time work as a linear function of the state variables:

$$\begin{aligned} V^*_{f,t} = {} & \beta_o + \beta_1 age + \beta_2 age^2 + \beta_3 educ + \beta_4 race + \beta_5 AFQT + \beta_6 f_{t-1} + \beta_7 E_t + \beta_8 t \\ & + \overline{\beta}_9 \tau_{st} + \beta_{10} BW + \beta_{11} gender + \beta_{12} I[age < 20] + \beta_{13} I[age \geq 33] + \beta_{14} EXPBEF \\ & + \beta_{15} workbef + \beta_{16} C_t + \beta_{17} D_t + \beta_{18} NC_t + \beta_{19} I[C_t = 0] + \beta_{20} I[t = 1] \\ & + \beta_{21} I[t < 5] + \beta_{22} I^c_{t-1} + \overline{\beta}_{23} R_{st} + \beta_{24} \theta_{st} + \varepsilon^*_{ft} \end{aligned} \tag{11}$$

Here, $\overline{\beta}_9$, $\overline{\beta}_{23}$, β_{24} are parameters that multiply the State/time specific local demand conditions, τ_{st}, welfare rules, R_{st}, and child care spending, θ_{st}, whose important role in providing exclusion restrictions we stressed earlier. While we abstracted from multiple children in Section 4.1, here we include NC_t, the number of children younger than 18. Finally we let $\varepsilon^*_{ft} = \mu_f + \nu_{ft}$.

The linear approximation to the value function for part-time work is similar, except it has coefficients that go from β_{25} to β_{50} and a stochastic term $\varepsilon^*_{pt} = \mu_p + \nu_{pt}$.[43] Then, normalizing the value function for No-Work to 0, and assuming that ν_{ft} and ν_{pt} are jointly normally distributed, we obtain a multinomial probit (MNP) model. In forming the likelihood function, we simulate the MNP choice probabilities using the GHK probability simulator (see Keane (1994)).

Similarly, the decision rule for child care is approximated by a probit where the value function for use of child care V_c^* is a linear function of all the state variables, with associated coefficients β_{51} to β_{76} and a stochastic term $\varepsilon^*_{ct} = \mu_c + \nu_{ct}$ that has a N(0,1) distribution.

Next, we write the initial and re-employment wage equations:

$$ln\, w_0 = \beta_{97} + \beta_{98} educ + \beta_{99} age + \beta_{100} age^2 + \beta_{101} race + \beta_{102} AFQT + \overline{\beta}_{103} \tau_{so} + \varepsilon^*_{w0}$$

$$\begin{aligned} ln\, w_t = {} & \beta_{104} + \beta_{105} educ + \beta_{106} age + \beta_{107} age^2 + \beta_{108} race + \beta_{109} AFQT + \beta_{110} \cdot t \\ & + \beta_{111} E_t + \beta_{112} f_{t-1} + \beta_{113} p_{t-1} + \beta_{114} (E_t \cdot educ) + \overline{\beta}_{103} \tau_{st} + \varepsilon^*_{wt} \end{aligned} \tag{12}$$

where $\varepsilon^*_{wt} = \mu_w + \nu_{wt}$, and μ_w is the unobserved skill endowment of the mother.

[43] The only difference is that V_f^* depends on lagged full-time while V_p^* depends on lagged part-time. Keane (1992) shows that error correlations in the MNP are practically impossible to identify without such exclusion restriction. Nevertheless, the probability of full and part time work in the model are functions of all the state variables.

Finally, we write the key equation of interest, the cognitive ability production function:

$$\begin{aligned}\ln S_t &= \ln A_o(\mu_s) + \beta_{77} C_t + \beta_{78}(C_t \cdot \ln A_o(\mu_s)) + \beta_{79} I_t + \beta_{80}(I_t \cdot \ln A_o(\mu_s)) \\ &\quad + \beta_{81} \cdot t + \beta_{82} NC_t + \beta_{83} d_{1t} + \beta_{84} d_{2t} + v_{st}\end{aligned} \tag{13}$$

where:

$$\begin{aligned}ln\, A_o(\,\mu_s\,) &= \beta_{85} + \beta_{86} AFQT + \beta_{87} educ + \beta_{88} race + \beta_{89} age + \beta_{90} age^2 + \beta_{91} BW + \\ &\quad \beta_{92} I[\,age < 20\,] + \beta_{93} I[\,age > 33\,] + \beta_{94} gender + \beta_{95} EXPBEF + \\ &\quad \beta_{96} I[\,worked\ bef\,] + \mu_s\end{aligned}$$

where $\varepsilon^*_{st} = \mu_s + v_{st}$. Recall that A_o is the child's initial skill endowment, of which μ_w is the unobserved component, and d_1 and d_2 are test dummies (i.e., PPVT or PIAT-Math). Note that (13) includes interaction terms between the inputs and the ability endowment that we mention in section 4.1 but did not include explicitly in equations (6)-(7) and (9) to simplify the exposition.[44] This allows for heterogeneity in effects of child care and income on child outcomes. Table 2 summarizes the control variables we include in the child cognitive ability production function.

We assume the permanent error components $\{\mu_f, \mu_p, \mu_c, \mu_s, \mu_w\}$ have a joint normal distribution F(μ). Allowing correlation of the time invariant unobservables across the 4 equations of the system (i.e., the MNP for work, the probit for child care, the wage equation and the test score equation) is the mechanism through which joint estimation corrects for selection bias.

From this setup it is easy to see the exclusion restrictions that constitute one of the identification strategies in the quasi-structural dynamic selection model. These are summarized in Table 3. Most critically, note that the state and time specific welfare and child care subsidy rule parameters R_{st} and θ_{st} and the local demand condition variables, τ_{st}, enter the decision rules for work and day care utilization, but do not enter the cognitive ability production function. Similarly, the state and time specific welfare and child care subsidy rule parameters R_{st} and θ_{st} do not enter the wage equation (although, of course, the local demand condition variables do).

In addition, the structure of the model delivers additional exclusion and functional form restrictions, because the reduced form decision rules for work and child care <u>must</u> depend on all the state variables of the model, while the cognitive ability production function and wage equations are determined by structural assumptions. For example, lagged full and part time work,

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[44] (13) also includes *NC*, the number of children under 18, which we ignored in Section 4.1 to simplify exposition.

as well as work experience, enter the decision rules for work and day care use because they are assumed in equation (4) to affect offer wages. But they do not enter the child cognitive ability production function directly. Under our structure, the assumed inputs to the production function are: (i) cumulative time that the child spends with alternative care providers rather than the mother, and (ii) the mother's cumulative income since childbirth. Thus, total work experience and lagged full- and part-time work affect cognitive outcomes only via their effects on (i) and (ii). This is an exclusion restriction delivered by our structure. Similarly, cumulative welfare participation (D_t) enters the decision rules for work and child care because it affects incentives to work and/or participate in welfare. But under our structural assumptions it is excluded from entering the cognitive ability production function (or the wage function) directly.

Of course, an alternative to estimating the quasi-structural dynamic selection model described here is the even simpler single equation IV approach; i.e., estimate the cognitive ability production function alone, using instruments for cumulative income (I_t) and child care use (C_t). As the sequential choice model is not made explicit, the instruments need to capture average incentives to work and use day care from birth up until time t. For instance, one might somehow average the welfare and child care subsidy rule parameters over the period, or use many lagged values. In Bernal and Keane (2006) we try various different approaches, as we discuss below.

Finally, it is worth emphasizing that using data on women with multiple children is rather difficult in a fully structural approach, for reasons we discussed earlier (i.e., one would need to model how the mother allocates time and income among children). But in quasi-structural or linear IV approaches, it is simple to include the main effect of number of children in the test score and other equations of the system, as well as interacting I_t and C_t with number of children to allow effects of income and day care use to depend on number of children. Prior non-structural work in this area has generally not discussed this issue, or included such interactions. We will experiment with such interactions below.[45] A related point is that prior non-structural work has generally included married and single women in the same sample when estimating effects of maternal time or day care on child outcomes. Clearly, the assumption that marital status does not substantially alter the relationships of interest is quite strong.

[45] Also note that number of children may itself be endogenous in the child cognitive ability production function (e.g., if there is a quality/quantity tradeoff). In a single equation IV approach one can instrument for number of children and its interaction terms, as in Bernal and Keane (2006). Our quasi-structural model attempts to control for this via the correlation between the μ's. For example, if women with many children also tend to have skill endowments, they will then tend to have low μ's in the wage equation.

5. The NLSY Data

5.1. Individual Data

We use data from the National Longitudinal Survey of Youth (NLSY) 1979 youth cohort. This consists of 12,686 individuals, approximately half of them women, who were 14-21 years of age as of January 1, 1979. It includes a core random sample and an oversample of blacks, Hispanics, poor whites and the military. Interviews have been conducted annually since 1979. On a regular basis, the NLSY79 has collected pre- and postnatal care information from the sample of women as they became mothers. In 1986 a separate survey of all children born to NLSY79 female respondents began. The child survey includes a battery of child cognitive, socio-emotional, and psychological well-being questions have been administered biennially for children of appropriate age, including the tests we use in our analysis.

Using the NLSY 79 Workhistory File, we construct a detailed employment history for each mother in the sample for the period surrounding the birth of her child, i.e., up to four quarters before birth and each quarter interval since the child's birth for a period of five years. We use the geocode data to identify the State of residence of each individual in order to be able to construct State specific welfare rule parameters and measures of local demand conditions.

For child care, retrospective data were gathered during 1986, 1988, 1992, and 1994-2000 that allow us to construct complete child care histories during each of the first three years of the child's life. In addition, data on whether the mother used child care or not during the 4 weeks prior to the interview date are available for the 1982-86, 1988, 1992 and 1994-2000 survey years. This allows us to construct partial histories of child care for the fourth and fifth years after birth.

Estimation of the quasi-structural model of section 4.2 requires a sample of women that are single (i.e., who did not cohabitate with a male co-resident) during five years following child birth, and for whom we observe at least one child test score. 1,464 mothers in the NLSY satisfy these requirements, and we have 3787 test score observations on their children.

Of these women, 245 had children between 1990 and 2000, so waivers and TANF impact their labor supply/child care decisions before the children reach school age. Much of our leverage for identification comes from comparing outcomes for these children with those for the 1,219 children born too early for their mothers' behavior to be impacted by these major welfare rule changes. However, it is important to note that even in the pre-reform period some of our instruments, like AFDC grant levels and local demand conditions, varied greatly across States and over time, also providing an important source of identification. And, in the post-reform period, we also get leverage for identification by comparing children in States with “strict” vs. “lenient” welfare rules.[46]

In Table 4 we compare mean characteristics of the single mothers in our sample with those of all single mothers, as well as all mothers, in the NLSY. The single mothers in our sample are very similar to the sample of all single mothers in the NLSY, despite our screen that the mother remains single for 5 years after childbirth, and our various missing data screens. Of course, the single mothers are quite different from the sample of all mothers They are younger (by 1.7 years), less educated by 0.8 years, much more likely to be Hispanic or black (83% vs. 47%), have a lower average wage before childbirth ($4.39 vs. $6.32 in 1983$).

Figure 1 displays employment and child care choices for 5 years after birth for women in our sample. During the first quarter after birth, about 73% of single mothers stay at home and do not use child care. The remainder use child care, with 10% working full-time, 5% part-time and 12% staying home. By the end of 16 quarters, only 38% continue to stay at home and not use child care. 29% work full-time, 17% part-time and 26% stay home and use child care.

5.2. Maternal Time Inputs, Income and Child Assessments

Unfortunately, the NLSY does not report the amount of time that a child is in child care (rather than maternal care). It only contains an indicator for whether the mother used child care for at least 10 hours per week during the last month.[47] This information in itself is not adequate to determine whether a child was in child care full-time or only part-time. However, by combining the child care variable with maternal work history information, we can make a reasonable determination about whether child care was full or only part-time.

Thus, we use the child care variables, in conjunction with the work history data, to construct: (i) a dichotomous indicator of child care use, I_t^c, for purposes of estimating the child care probit, and (ii) a more refined measure of whether the mother used full-time, part-time or no

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[46] A possible threat to validity of the welfare rule instruments is that rules may be correlated with women’s skill levels. For example, high skilled women might tend to live in States with stricter rules, or States that moved towards welfare reform first. In Appendix 3 we present pre-reform average scores by States depending on whether the State implemented a Welfare Waiver prior to 1996, and whether the State implemented stricter rules after 1996. Note that there is no significant difference in average test scores across the different types of States. Indeed, the point estimates suggest that States with higher average test scores were *more* likely to adopt waivers or to have stricter rules. This is opposite to the bias one would worry about. See also Bernal and Keane (2006) for further discussion.

[47] In ‘82, ‘83 and ‘84, mothers were asked how many hours the youngest child was in daycare. But there is a serious missing data problem (e.g., only 115 of the 1,464 mother-child pairs in our sample have non-missing data in 1982).

child care, which we use to construct and the child care usage measure C_t that appears in the cognitive ability production function (13).

Specifically, if a woman reported using at least 10 hours per week of child care, she is assumed to have used child care during the quarter.[48] We assume that if she worked full-time (375+ hours in the quarter) then the child care must have been full-time, which seems straightforward. On the other hand, if the mother did not work (<75 hours in the quarter) but still reported using child care, it seems highly likely that the child care usage was only part-time. More difficult is making a reasonable assignment if the mother worked part-time (75-375 hours in the quarter). We decided to assume the child care was part-time in this case. We admit this assignment is not as obvious. However, when we experimented with assigning full-time day care in this case, we found that it had almost no effect on the results. Thus, we define the function:

$$h_t^c = \begin{cases} 1 & \text{if mother works full – time and used child care} \\ 0.5 & \text{if mother works part – time and used child care} \\ 0.5 & \text{if mother did not work and used child care} \\ 0 & \text{otherwise} \end{cases} \tag{14}$$

and form cumulative child care, $\hat{C}_t$, average child care, $\overline{C}_t$, and current child, I_t^c,as follows:

$$\hat{C}_t = \sum_{\tau=1}^{t} h_\tau^c, \quad \overline{C}_t = \frac{1}{t}\sum_{\tau=1}^{t} h_\tau^c \quad \text{and} \quad I_t^c = I[h_t^c > 0]$$

where t is the age of the child.

As we noted earlier, complete child care histories are only available for three years after childbirth. Thus, we impute child care choices in years 4 and 5 after childbirth based on current work and work/child care histories. First, we set h_t^c=1 or 0.5 for mothers who work full or part-time, respectively, in a given period t after the third year. Second, for mothers who do not work in a given period t, we impute the child care choice based on the predicted probability of using child care from a probit model that we estimate using observed work and child care histories. As the probit coefficients in Appendix 1 indicate, day care use by non-working mothers is well predicted by (i) having used day care a lot in the past and (ii) having not worked a lot since child birth. The pseudo R-squared is very large, suggesting these are excellent predictors.

[48] Types of child care include formal care in a day care center, nursery school or preschool, as well as informal care by a relative or non-relative.

Another input into the child cognitive ability production function (13) is real household income. We measure it by summing income from all sources including wages, public assistance, unemployment benefits, interest or dividends, pension, rentals, alimony, child support and/or transfers from family or relatives. Household income is deflated using a region-specific CPI, just as we did for welfare benefits (see Section 3.3), to account for differences in costs of living across metropolitan areas. We then construct cumulative real income since childbirth.

The child cognitive ability measures from the NLSY79 that we use as the dependent variable in (12) are scores on the Peabody Picture Vocabulary Test (PPVT) at age 3, 4 and 5, and the Peabody Individual Achievement Test Reading Recognition subtest (PIAT-R) and Mathematics subtest (PIAT-M) at ages 5 and 6. Both assessments are among the most widely used for preschool and early school-aged children. The PPVT is a vocabulary test for standard American English and provides a quick estimate of verbal ability and scholastic aptitude. The PIAT-M measures attainment in mathematics. It consists of eighty-four multiple-choice items of increasing difficulty. It begins with such early skills as numeral recognition and progresses to measuring advanced concepts in geometry and trigonometry. Finally the PIAT-R measures word recognition and pronunciation ability.

Appendix 2 contains descriptive statistics for test scores in our sample. Note that there is no clear age pattern in the mean scores, as they are age adjusted. Mean scores on the PPVT, PIAT-M and PIAT-R are roughly 80, 95 and 101. Standard deviations seem to vary more by age than by test. For instance, at 5, the one age where we see all three tests, the standard deviations are quite similar: 17.5, 14.3 and 15.3, respectively. Thus, we decided to merge information from the three tests, allowing for mean differences.

5.3 Descriptive Statistics

In Table 5 we present means and standard errors of the variables used in the analysis. The mean log test score in the sample is 4.50 with a standard deviation of 0.22. This drops to 0.186 when mean differences across tests are adjusted. 64% of women in the sample worked prior to giving birth at an average hourly rate of $4.39 (1983 $). Average work experience prior to childbirth was 4.7 years, and 72% of women had never been married. Average annual household income was $10.9 thousand (1983 $). Finally, during the 20 quarters after childbirth the mothers use child care 35.5% of the time, for a total of 7.1 quarters on average.

6. Estimation Results

6.1. Estimation Results for the Quasi-Structural Model – Homogenous Effects Case

In this section, we present parameter estimates for the "quasi-structural" model of Section 4.2. That is, we jointly estimate approximate decision rules for work and child care use, obtained from the structural model of section 4.1, with the child cognitive ability production function and maternal wage functions. Specifically, we maximize the likelihood given by approximate decision rules for work and day care (see equation (11)), and the wage and test score density functions implied by equations (12) and (13).

In Table 6 we present estimates of the cognitive ability production function in equation (13) by several estimation methods. Columns (1) and (2) present OLS and RE estimates respectively. Column (3) presents linear IV estimates, in which the welfare and child care subsidy rules and local demand condition variables in Table 1 are used as instrumental variables.[49] Finally, column (4) presents the estimates obtained from maximum likelihood estimation of a special case of our "quasi-structural" model, in which we assume the effects of child care and income on child outcomes are homogenous across types of children and mothers.

The OLS results imply that use of child care has no significant effect (either statistically or quantitatively) on children's achievement. The random effects estimates are similar. However, the linear IV estimates imply that the OLS and RE estimates are severely upward biased. The linear IV estimate implies that one-quarter of full time work and child care use reduces a child's test scores by 0.81 percent. This translates into an effect of –3.2% for each year of child care. The ML estimates of the quasi-structural model imply a similar result: that an additional quarter of child care leads to a reduction of about 0.70 percent in a child's test scores. This implies that one year of full-time maternal work and child care use reduces a child's test scores by roughly 2.8%, which is (.0279/.186)=0.15 standard deviations of the score distribution.

It is interesting that the linear IV and quasi-structural estimates are so similar. The linear IV estimates rely on the welfare and day care subsidy rules, along with local demand conditions

[49] As we discussed in Section 4.2, linear IV requires that we construct instruments that capture effects of welfare rules and local demand conditions from the birth of the child up through time t on cumulative child care use C_t and cumulative income I_t. To do this, in the first stage of our 2SLS procedure, we let C_t and I_t depend on welfare rules and local demand conditions from the birth of the child up thought age t. Thus, the number of instruments grows with age of the child. To conserve on parameters, we assume the instruments have the same coefficients at each age. In Bernal and Keane (2006), we consider various alternative assumptions (e.g., allowing effects of the instruments to differ by age), and show it has little effect on the results.

as instrumental variables. The quasi-structural approach relies on the same instruments to provide exclusion restrictions, and, in addition, uses additional exclusion/functional form restrictions implied by the structure of the model (see Table 3 and the discussion in Section 4.2). Thus, each approach relies on somewhat different identifying assumptions – particularly in terms of the exact form of the decision rules for work and child care (whose form the IV approach leaves implicit) – and hence, each implements the selection correction (for the problem that children placed in day care may differ those who are not) in a somewhat different way. Thus, it is comforting that results are so robust across the two approaches.

The effect of cumulative household income is not statistically significant under any of the estimation methods except the quasi-structural approach. However, the estimated effect of household income since the birth of the child is quantitatively very small. In particular, a 1% increase in cumulative household income is associated with an increase of 0.019% in child's test scores, which is equivalent to (.000192/.1861) = 0.001 standard deviations. This effect appears especially small if we compare it with the estimated child care effect. For example, if cumulative household income were to double, e.g. because the mother decides to work twice as much during the period since the birth of the child, then that extra income would be associated with a 1.9% increase in the child's scores (or .0192/.186 = .10 standard deviations). However, the negative effect of <u>each</u> additional year of child care use (required because the mother worked full-time) is almost 50% greater, i.e., 2.8%. That means that while income has a positive effect on the child's achievement it does not come close to completely offsetting the effect of maternal separation.

Given that we include controls for maternal education and AFQT, this result is consistent with a view that permanent income is significant in determining parental investment in children, and hence the children's achievement, while transitory income is less relevant.

Finally, it is notable that interactions between number of children and either cumulative day care or cumulative income, which we discussed in Section 4, were not significant in any specification. Thus, we elected to include only main effects of children in the models we report.

One advantage of the quasi-structural approach over the simpler single-equation linear IV approach is that, by explicitly estimating the work and child care decision rules, and by including the mother's wage function as part of the system, we achieve a rather substantial efficiency gain. Indeed, the standard error on the cumulative childcare use coefficient in the log test score equation falls by a factor of 7.4 (from .00333 to .00045), giving us much greater confidence in the estimated effect size. As we'll see below in Table 12, this arises in part because the wage equation residual (i.e., the mother's unobserved skill endowment) conveys a great deal of information about the unobservable in the test score equation.

In general, the point estimates are very similar for all the variables in columns (3) and (4) of Table 6. Yet, in almost every instance, the standard errors on the quasi-structural estimates are much smaller than those for the IV estimates. Thus, by imposing some structure we obtain an efficiency gain while getting estimates that are very close to linear IV.

6.2. Estimation Results for the Quasi-Structural Model – Heterogeneous Effects Case

6.2.A. Estimates of the Test Score Equation

A key advantage of the quasi-structural approach over linear IV is that we can accommodate unobserved heterogeneity in the effects of the inputs (i.e., child care time and household income) on child cognitive outcomes. In Tables 7 through 12 we report estimates of the full model that includes the interactions between initial child ability ($ln\ A_0$) and both cumulative child care and household income that appear in equation (12).

The main results for the cognitive ability production function are presented in Table 7 column (2). The interaction term between cumulative child care and the child ability endowment is negative and statistically significant, suggesting that replacement of maternal time with day care time has a more negative effect on outcomes for children with higher ability endowments. In other words, maternal time and child ability endowment are complements in child cognitive ability production. However, the inclusion of both the linear term in cumulative child care and its interaction with $ln\ A_0$ makes the estimates difficult to interpret.

Hence, in Table 8, we report descriptive statistics about the estimated ln A_0, (i.e., mean, standard deviation, minimum, maximum), which help one interpret the quantitative importance of the interactions. And, in Figure 2, we plot derivatives of log scores with respect to cumulative child care and income, as a function of $ln\ A_0$. The graph indicates the values of the derivatives at the mean of $ln\ A_0$, and at plus and minus two standard deviations of the mean.

At the mean of the data (i.e, the mean child ability endowment), the estimated effect of an additional quarter of full-time maternal work and child care use is -.67%, which translates into an effect of roughly –2.7% per year (about 0.14 std. dev. of the score distribution). It is interesting that this mean effect is almost identical to what we obtained in the homogenous effects model of Table 6 column (4), and similar to the effect we estimated using linear IV in Table 6 column (3).

In Figure 2 we also show estimated effects for children that are 2 standard deviations above and below the mean ability endowment. The effect of child care ranges from -.52% per quarter (-2.1% per year) for a child with an ability endowment two standard deviations below the average to -.83% per quarter (-3.3% per year) for a child with an ability endowment two standard deviations above the average. Note that the interaction between income and $ln\ A_0$ is both statistically and quantitatively insignificant.

The third column of Table 7 reports a special case of the model that accommodates only observed but not unobserved heterogeneity in the effect of day care. Here, we interact mother's education, one of the determinants of the latent child ability endowment A_0, with cumulative child care. The interaction is highly significant (t=-6) and negative, implying that the replacement of mother's time with alternative day care providers time has a more negative effect on child cognitive outcomes for more educated mothers.

Since maternal education is observed, we can de-mean this variable prior to interacting it with cumulative child care. Hence, in column (3), the linear child care term is still interpretable as the effect of child care on child outcomes for a mother with average education (11.2 years). This estimate is -.69% per quarter, or –2.8% per year. The interaction term is -.12% per quarter (or -.48% per year), implying that, for a mother with only 9.2 years of education, the negative effect of a year of child care use is –2.8 + (2)(-.48) = -1.8% per year. Thus, the adverse effect of child care use is much smaller for less educated mothers.

Bernal and Keane (2006) obtain very similar point estimates using linear IV, i.e., a linear day care effect of -.00702 and an interaction with mother's education of -.00125. But the interaction has a standard error of .0007 and hence is only significant at the 10% level, preventing them from drawing strong conclusions. Thus, the increased efficiency of the quasi-structural approach (which reduces the standard error by a factor of roughly 3.5) is important for obtaining the clear conclusion that day care has a less adverse effect for less educated mothers.

6.2.B. Estimates of the Work, Child Care and Wage Equations

We next discuss the estimates of the other three equations of the quasi-structural system. First, in Table 9 we present estimates of the initial and re-employment wage equation. All parameters show the expected sign and reasonable magnitudes. For example, one additional year of education is associated with 4% increase in initial wages. Similarly, the age and age^2 coefficients together imply that, at age 20, an additional year of labor market experience (i.e., age) is associated with a 4.5% increase in the initial wage.[50] The three local demand condition variables are highly significant and with the expected signs.

Tables 10 and 11 present estimates of the work and child care probits. The estimated effects of welfare rules are generally reasonable. If a State has a time limit or work requirement, it increases the probability of work (especially part-time), and also the probability of day care use (although the latter effect is only marginally significant). The indicator for whether the woman might be subject to a time limit or work requirement, I[TL_HIT or WR_HIT] has a large and highly significant positive coefficient in the value functions for both full- and part-time work and child care utilization.[51] A longer benefit receipt time limit in her State of residence significantly reduces the probability that the mother works, although the effect on day care is insignificant. A longer work requirement time limit significantly reduces the probability that a mother works part-time. The number of work requirement exemptions (a measure of strictness of State welfare policy) has a large and highly significantly negative effect on the probability that a mother works full-time, and lowers the probability of using day care. As one would expect, both the flat earnings disregard and the percentage disregard increase the probability that a mother works.

The EITC phase-in rate increases the probability of part-time work, while decreasing that of full-time work. This result is consistent with previous findings by Keane and Moffitt (1998), who simulate the effect of an EITC-type of policy and find it encourages part-time work relative to full-time work. EITC is also significant and positive in the probit for day care. Interestingly, the Child Support Enforcement (CSE) program expenditure per single mother (ENFORCE) has a highly significant positive effect on both work (especially part-time) and day care use. Theoretically, effects of CSE on work are ambiguous (see Fang and Keane (2004)).

Turning to the local demand conditions, the 20th percentile wage in the woman's State of residence significantly increases the probability of full-time work and reduces the probability of part-time work. In addition, the percentage of the population employed in the services sector significantly increases the probability of work.

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[50] The standard errors on age and age^2 are very large because they are highly collinear due to the young age and fairly limited age range of the sample. But they are jointly significant.

[51] Due to collinearity between the indicators for whether a State had a time limit and whether it had a work requirement (i.e., if a State has one, it almost always has the other), we were forced to combine the variables TLI and DWR into a single indicator for whether a State had either a work requirement or a time limit. A similar collinearity problem forced us to combine the indicators for whether the woman could have potentially been hit by a binding time limit or work requirement, TL_HIT and WR_HIT, into a single indicator for whether the woman could potentially have been hit by either a time limit or a work requirement.

Some of the estimates are less intuitive. Higher welfare grant levels are associated with a higher probability of work and a lower probability of day care. Greater (minimum) remaining welfare eligibility is associated with a higher probability of working. Local unemployment rates are insignificant. The effect CCDF expenditures on probabilities of working and using child care are negative. This might arise because the program design encourages welfare participation (i.e., in some States there are no co-pays for welfare recipients, or former recipients).

Among the most interesting parameters are the error correlations, reported in Table 12, as these implement the selection correction for the type of children placed in day care. Note that the correlation between the permanent unobservables in the test score and mother's wage equation is -.69, implying, somewhat surprisingly, that mothers with high unobserved skill endowments tend to have children with relatively low unobserved ability endowments.[52] On the other hand, the permanent unobservable in the full and part-time work equations are positively correlated with the child's unobserved ability endowment. Thus, working mothers tend to have relatively high skilled children, biasing OLS estimates of work/day care effects in a positive direction. The permanent error component in the child care equation is very small, so it has little effect.

6.3. Model Fit

Figure 3 shows the fit of the quasi-structural model to the choice distributions in Figure 1, based on 15,000 simulated individuals. The model matches the choice frequencies in the data quite well, particularly for the most common alternatives, i.e., stay at home and do not use childcare and work and use child care. Chi-squared goodness-of-fit test statistics shown in Table 13 confirm the graphical results. The only mild rejections are in the 9th and 11th quarters after childbirth, and these occur because, at those ages, the model slightly understates the percent who stay home and use child care. Predicted wages by mother characteristics and predicted log average test scores by child's age (shown in Figure 4 and Table 14) fit the data closely as well.

7. Conclusions

This paper evaluates the effects of maternal work and child care use on children's cognitive development, using the sample of single mothers in the National Longitudinal Survey of Youth (NLSY). In particular, we assess the effects of maternal work/child care on child cognitive test scores recorded at ages 3, 4, 5 and 6. To deal with potential bias created by

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[52] This is less surprising given that the mother's observed skill endowment controls for her education and AFQT.

unobserved heterogeneity of mothers and children, and systematic selection of certain types of children into childcare, we develop a model of mother's employment and child-care decisions. Guided by this model, we obtain approximate decisions rules for employment and child care use, and estimate these jointly with the child's cognitive ability production function – a "quasi-structural" approach. This joint estimation implements a dynamic selection correction.

To help identify our dynamic selection model, we take advantage of plausibly exogenous variation in employment/child-care use created by variations in welfare rules and local demand conditions across States and over time – especially the large changes created by the 1996 welfare reform and earlier welfare waivers. These welfare rules and local demand conditions provide natural exclusion restrictions, as it is plausible that they enter the decision rules for employment and day care use, while not entering the child cognitive ability production function directly. These instruments are quite powerful, in the sense that they explain a substantial part of the variation in work and day care use by single mothers.

Our results imply that if a mother works full-time, while placing a child in day care, for one full year, this reduces the child's cognitive ability test score by 2.7% on average, which is roughly 0.14 standard deviations of the score distribution.[53] We estimate an almost identical effect in a simple linear IV approach based on the same instruments. Each approach implements a selection correction (for the problem that children placed in day care may differ those who are not) in a somewhat different way. Thus, it is comforting that results are so robust across the two approaches. However, the quasi-structural approach leads to a substantial efficiency gain, reducing the standard error on the day care effect by a factor of roughly 7.4 and giving us much greater confidence in the estimate.[54]

The other advantage of the quasi-structural approach is that it easily accommodates unobserved heterogeneity in the effect of interest. We do find substantial heterogeneity. The effect of child care on test scores ranges from -2.1% per year for a child with an ability endowment two standard deviations below the average to -3.3% per year for a child with an ability endowment two standard deviations above the average. Observed heterogeneity is important as well. For, example, for a mother with average education (11.2 years) the effect of a year of child care is –2.8% per year, while for a mother with only 9.2 years of education, the

[53] The coefficient on full-time quarterly work/day care use in the log test score equation is -.00698 with a standard error of .00045 (t = -15.4). This implies an effect of -.028 per year. The standard deviation of log scores is .186.
[54] Using linear IV, the coefficient is -.00807 with a standard error of .00333 (t = -2.42).

negative effect of a year of child care use is –2.8 + (2)(-.48) = -1.8% per year.

We also find that the effect of household income since birth of the child is quantitatively small. In particular, a 1% increase in cumulative household income is associated with an increase of 0.019% in the child's test scores, which is equivalent to 0.001 standard deviations. This seems especially small when compared to the estimated child care effect. For example, if cumulative household income were to double (e.g., because the mother decides to work twice as much during the period since the birth of the child) then that extra income would be associated with a 1.9% increase in the child's scores. However, the negative effect of <u>each</u> additional year of child care use is almost 50% larger, i.e., 2.8%. Thus, while income has a positive effect on the child's achievement it does not come close to offsetting the effect of maternal separation.

One should be careful not to interpret this result as saying income doesn't matter. Given that we include controls for maternal education and AFQT, this result is consistent with a view that permanent income is significant in determining parental investment in children, and hence the children's achievement, while transitory fluctuations in income are much less relevant.[55]

Our study of the case of single mothers extends earlier work by Bernal (2005), who estimated the effects of maternal time inputs on children of married women in the NLSY. Using a fully structural approach, she found that one-year of maternal full-time work and child-care results in a 2% reduction in child cognitive ability test scores. A key motivation of our work was to see if that result generalized from married to single mothers. Our estimate for single mothers is larger (2.7%), but the similarity of the results is fairly striking. Bernal (2005) also found heterogeneity in child care effects with child ability similar to what we find here.

Obviously, aside from the technical advantage that arises because of the presence of highly plausible instruments (i.e., the welfare rules and local demand variables that have large effects on their behavior), the study of single mothers is of special policy interest as well, given that recent welfare policy changes have substantially increased their work and day care use. Since we find that maternal work and day care use has negative effects on test scores for children of single mothers, it suggests an aspect of cost of these policies that needs to be considered when evaluating their overall success.

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[55] The finding of small effects of income is reminiscent of findings in Blau (1999b), that household income has small effects on outcomes for young children after controlling for family background characteristics like parental education. It is also reminiscent of findings in Cameron and Heckman (1998) to the effect that permanent income largely determines parental investments in children, with transitory income fluctuations playing a minor role (although their results are for school age rather than pre-school children)

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Table 1

List of Instruments

Variable	Description
	Time Limits
TLI_{st}	Dummy for whether state s has time limit in place in period t.
TL_LENGTH_{st}	Length of time limit in state s in period t.
TL_HIT_{ist}	Dummy variable indicating whether a woman would have hit time limit
$REMAIN\_TL\_ELIG_{ist}$	Minimum potential remaining length of a woman's time limit, constructed: TL_LENGTH_{st}-min$\{AGE_OLDEST_CHILD_{ist}, ELAPSED_TL_{st}\}$
$REMAIN\_CAT\_ELIG_{ist}$	Remaining length of time to be categorically eligible for welfare benefits: 18-$AGE\_YOUNGEST\_CHILD_{ist}$
	Work Requirements
DWR_{st}	Dummy for whether state s has work requirement in place in period t.
WR_LENGTH_{st}	Length (in months) of work requirement limit in state s in period t.
WR_HIT_{ist}	Indicator for whether a woman could be subject to a work requirement: =1 if[$WR\_LENGTH_{st} \leq \min\{AGE\_OLDEST\_CHILD_{ist}, ELAPSED\_WR_{st}\}$ & $AGE\_YOUNGEST\_CHILD_{ist} \geq AGE\_CHILD\_EXEM_{st}$]
$AGE\_CHILD\_EXEM_{st}$	Age of youngest child below which the mother will be exempted from work requirement in state s at time t.
$EXEMP_{st}$	Number of work requirement exemptions in state s
	Earnings Disregards
$FLAT\_DISREGARD_{st}$	Flat amount of earnings disregarded in calculating the benefit amount.
$PERC\_DISREGARD_{st}$	Benefit reduction rate (Does not include phase-out)
	Other Policy Variables
BEN_{ist}	Real AFDC/TANF maximum benefits, calculated using the state (dollars) level benefit rule and the mother's family composition.
$EITC_{ist}$	EITC phase in rate constructed from both the federal and state level
$CCDF_{st}$	CCDF expenditure per single mother in state s at time t ($thousands)
$ENFORCE_{st}$	Child support enforcement expenditure in state s at year t per single mother ($thousands)
	Local Demand Conditions
UE_{st}	Unemployment rate in State s in period t
$SWAGE_{st}$	Hourly wage rate at the 20th percentile of the wage distribution in State s in period t.
$SERV_{st}$	Percentage of the State s labor force employed in services in period t.

$ELAPSED\_TL_{st}$: time in months elapsed since the implementation of time limit.

$ELAPSED\_WR_{st}$: time in months elapsed since the implementation of work requirement.

Table 2

Control Variables in the Cognitive Ability Production Function

Variable	Description
Baseline Specification	
$EDUC_i$	Mother's educational attainment at childbirth
$AFQT_i$	Mother's AFQT score
$I[AFQT\ missing]_i$	Dummy for whether AFQT score is missing
AGE_i	Age of the mother at childbirth
AGE_i^2	Age of the mother at childbirth squared
$I[AGE_i<20]$	Dummy for whether mother is younger than 20 years old
$I[AGE_i>=33]$	Dummy for whether mother is older than 33 years old
$I[workbef]_i$	Dummy for whether mother worked prior to childbirth
$EXPBEF_i$	Mother's total work experience (in number of years) prior to childbirth
$NSIB_i$	Number of siblings
$RACE_i$	Child's race (1 if black/hispanic, 0 otherwise)
$GENDER_i$	Child's gender (1 if male, 0 if female)
BW_i	Child's birthweight (ounces)
$AGECHILD_i$	Child's age at assessment date
$dPPVT_i$	Dummy for whether the corresponding test is PPVT
$dMATH_i$	Dummy for whether the corresponding test is PIAT-MATH
Alternative specifications also include	
$C_{ti} * lnA_{oi}$	Cumulative child care use interacted with child's initial skill endowment
$I_{ti} * lnA_{oi}$	Cumulative household income use interacted with child's initial skill endowment
$C_{ti} * EDUC_i$	Cumulative child care use interacted with mother's education
$I_{ti} * EDUC_i$	Cumulative household income use interacted with mother's education

Table 3

Exclusion Restrictions in the Model

Variable	Description	Full-time decision	Part-time decision	Child care decision	Wage Equation	Outcome Equation
age	Age of mother at childbirth	X	X	X	X	X
age^2	Age squared	X	X	X	X	X
education	Mother's education at childbirth	X	X	X	X	X
race	Child's race	X	X	X	X	X
f_{t-1}	I[worked full-time$_{t-1}$]	X		X	X	
p_{t-1}	I[worked part-time$_{t-1}$]		X	X	X	
AFQT	Mother's AFQT	X	X	X	X	X
AFQT missing	I[Mother's AFQT missing]	X	X	X	X	X
E_t	Mother's work experience	X	X	X	X	X
t	Time trend	X	X	X	X	X
UE	Unemployment rate	X	X	X	X	
SWAGE20	Average wage 20th percentile	X	X	X	X	
SERV	% employment in services	X	X	X	X	
BW	Birthweight	X	X	X		X
gender	Child's gender	X	X	X		X
NSIB	Number of siblings	X	X	X		X
I[age<20]	I[mother's age<20]	X	X	X		X
I[age>33]	I[mother's age>33]	X	X	X		X
EXPBEF	Experience before childbirth	X	X	X		X
workbef	I[worked before childbirth]	X	X	X		X
C_t	Cumulative child care	X	X	X		X
d_1,d_2	Test dummies					X
I[C_t>0]	I[Cumulative child care>0]	X	X	X		
I[t=1]	I[t=1]	X	X	X		
I[t<5]	I[t<5]	X	X	X		
I^c_{t-1}	Previous period child care choice	X	X	X		
BEN	Welfare benefits	X	X	X		
D_t	Cumulative welfare	X	X	X		
I[TLI or DWR]	Time Limit or Work Requirement	X	X	X		
TL_LENGTH	Time limit length	X	X	X		
I[TL_HIT or WR_HIT]	TL or WR might have hit	X	X	X		
REMAIN_TL_ELIG	Remaining months of TL eligibility	X	X	X		
REMAIN_ELIG	Remaining categorical eligibility	X	X	X		
WR_LENGTH	Work requirement length	X	X	X		
AGE_EXEM	Age of youngest child exemption	X	X	X		
EXEMP	Number of WR exemptions	X	X	X		
FLAT_DIS	Flat earnings disregard	X	X	X		
PERC_DIS	Percent earnings disregard	X	X	X		
ENFORCE	Child support enforcement expenditure	X	X	X		
EITC	EITC phase-in rate	X	X	X		
CCDF	CCDF expenditures	X	X	X		

Table 4
Mean Characteristics of Mothers in the Sample

Description	**All mothers in NLSY**	**Single mothers at childbirth only**	**Single mothers for 5 yrs after childbirth**	**Our Sample**
Mother's age at childbirth	24.8 (5.56)	23.56 (5.07)	23.80 (5.15)	23.13 (4.59)
Mother's education at childbirth (in years)	12.0 (2.475)	11.3 (1.920)	11.3 (1.917)	11.2 (1.909)
Mother's AFQT score	37.9 (27.23)	21.7 (20.09)	19.9 (19.11)	19.3 (18.30)
Hispanic or Black	0.47 (0.499)	0.73 (0.445)	0.79 (0.404)	0.83 (0.379)
Hourly wage before childbirth (first child)	6.32 (7.71)	4.74 (8.23)	4.90 (9.85)	4.39 (2.01)
Total number of children of mother	2.9 (1.37)	3.1 (1.57)	3.1 (1.61)	3.1 (1.53)
Father present at birth	0.55 (0.004)	-	-	-
Observations	4,814	2,528	1,820	1,464
Cases with wages at childbirth observed	3,274	1,620	1,102	941

Our sample screens are (1) The mother does not have a husband/partner for 5 years after childbirth and (2) The child has at least one test score observation.

Table 5
Summary of Variables used in the Empirical Analysis

Variable	Mean (standard error)
log(Test Score)	4.49855 (0.1861)*
Mother's education at childbirth	11.208 (1.8972)
Mother's age at childbirth	23.136 (4.5820)
Hispanic or Black	0.8262 (0.3790)
Birthweight (ounces)	111.97 (21.976)
Boys (Children of single mothers)	0.4976 (0.5001)
Mother worked before giving birth	0.6431 (0.4792)
Wage rate prior to giving birth	4.3938 (2.0075)
Accumulated work experience prior to giving birth (number of years)	4.7202 (6.0088)
Never married after childbirth	0.7215 (0.4483)
Separated after childbirth	0.1540 (0.3611)
Divorced after childbirth	0.1158 (0.3201)
Urban	0.8189 (0.3851)
Average Yearly Income (Thousands)	10.9274 (13.568)
Cumulative Income (Thousands)	51.1787 (67.415)
Average Child Care Use (% of periods)	0.3546 (0.3064)
Cumulative Child Care Use (Quarters)	7.0923 (6.1273)

*Standard error of log(test score) calculated after taking out the test-specific means of the three tests, i.e., the standard error of the residuals from a regression of log(test score) on test dummies PPVT and PIAT Math.

Table 6

Baseline Specification of the Score Equation

	(1) OLS	(2) RE	(3) I.V.	(4) M.L.E.
Cumulative Child Care	0.00054	0.00013	-0.00807	-0.00698
	(0.00077)	(0.00083)	(0.00333) **	(0.00045) **
Log(Cumulative Income)	-0.00263	-0.00403	0.02802	0.01919
	(0.00558)	(0.00570)	(0.02735)	(0.00218) **
Mother's education	0.01101	0.011475	0.013454	0.01298
	(0.00266) **	(0.00264) **	(0.00312) **	(0.00110) **
Mother's AFQT	0.00139	0.00138	0.00138	0.00132
	(0.00022) **	(0.00026) **	(0.00034) **	(0.00011) **
Mother's AFQT missing	0.05542	0.06422	0.06307	0.01962
	(0.01695) **	(0.02311) **	(0.01931) **	(0.01461)
Mother's age	-0.00930	-0.00465	-0.00515	-0.00356
	(0.01341)	(0.01388)	(0.01461)	(0.00555)
Mother's age squared	0.00016	0.00008	0.00006	0.00001
	(0.00027)	(0.00028)	(0.00030)	(0.00011)
I[mother's age<20]	0.01100	0.01626	0.00944	0.06867
	(0.01421)	(0.01646)	(0.01532)	(0.00661) **
I[mother's age>=33]	0.00231	0.00860	-0.00182	0.03464
	(0.03012)	(0.02999)	(0.03250)	(0.01216) **
I[worked before]	0.01052	0.01298	0.03511	0.02844
	(0.00916)	(0.00961)	(0.01344) **	(0.00376) **
EXPBEF	0.00110	0.00119	0.00336	0.00314
	(0.00109)	(0.00103)	(0.00176) *	(0.00040) **
Gender	-0.02329	-0.02275	-0.02474	-0.01688
	(0.00685) **	(0.00741) **	(0.00718) **	(0.00289) **
Race	-0.05011	-0.05502	-0.04053	-0.04614
	(0.01012) **	(0.01111) **	(0.01138) **	(0.00454) **
Birthweight	0.00450	0.00441	0.00591	0.05762
	(0.00619)	(0.00596)	(0.00638)	(0.00225) **
Number of siblings	-0.01695	-0.01748	-0.02801	-0.01590
	(0.00328) **	(0.00328) **	(0.00615) **	(0.00135) **
Child's age	0.02944	0.03262	0.03704	0.03779
	(0.00721) **	(0.00616) **	(0.01319) **	(0.00465) **
PPVT dummy	-0.25184	-0.25039	-0.25223	-0.22378
	(0.01015) **	(0.00817) **	(0.01032) **	(0.00832) **
PIAT math dummy	-0.07739	-0.07715	-0.07783	-0.05882
	(0.00395) **	(0.00588) **	(0.00398) **	(0.00986) **
Constant	4.58751	4.52602	4.43374	4.39550
	(0.15736) **	(0.17190) **	(0.18908) **	(0.07197) **
R^2	0.3745		0.3717	
MSE_{ML}	0.0304	0.0333	0.0305	0.0297
Fraction due to permanent	-	0.3352	-	0.2272

(1) Ordinarly Least Squares. Robust standard errors (Huber-White) by child clusters.
(2) Random Effects
(3) Instruments are policy variables and local demand conditions listed in Table 1. Assumes welfare rules and demand conditions have same effect in all years. Robust standard errors (Huber-White) by child clusters.
(4) Full quasi-structural model
** Significant at 5%; * Significant at 10%

Table 7

Test Score Equation - Model with Interactions

	(1)	(2)	(3)	(4)
Cumulative Child Care	-0.00698	0.02529	-0.00691	0.02499
	(0.00045) **	(0.0134) **	(0.0007) **	(0.0152) *
Log(Cumulative Income)	0.01919	0.01159	0.01700	0.01305
	(0.00218) **	(0.0862)	(0.0022) **	(0.0024) **
Childcare * $\ln A_o$		-0.00686		-0.00679
		(0.0029) **		(0.0033) **
Childcare * (Mother's education)			-0.00120	-0.00140
			(0.0002) **	(0.0002) **
Log (Income) * $\ln A_o$		0.001703		0.00137
		(0.01845)		(0.0004) **
Log (Income) * (Mother's education)			-0.00026	-0.00032
			(0.00096)	(0.0012)
Mother's education	0.01298	0.01297	0.01317	0.01316
	(0.00110) **	(0.0014) **	(0.0040) **	(0.0043) **
Mother's AFQT	0.00132	0.00132	0.00131	0.00132
	(0.00011) **	(0.0002) **	(0.0001) **	(0.0001) **
Mother's AFQT missing	0.01962	0.01956	0.01934	0.01971
	(0.01461)	(0.01489)	(0.01479)	(0.01551)
Mother's age	-0.00356	-0.00355	-0.00333	-0.00351
	(0.00555)	(0.0058)	(0.0056)	(0.0063)
Mother's age squared	0.00001	0.00001	0.00001	0.00001
	(0.00011)	(0.0001)	(0.0001)	(0.0001)
I[mother's age<20]	0.06867	0.06862	0.06880	0.06866
	(0.00661) **	(0.00858) **	(0.00660) **	(0.00787) **
I[mother's age>=33]	0.03464	0.03462	0.03468	0.03465
	(0.01216) **	(0.01335) **	(0.01230) **	(0.01440) **
I[worked before]	0.02844	0.02841	0.02841	0.02840
	(0.00376) **	(0.00413) **	(0.00377) **	(0.00413) **
EXPBEF	0.00314	0.00314	0.00314	0.00314
	(0.00040) **	(0.00047) **	(0.00040) **	(0.00047) **
Gender	-0.01688	-0.01687	-0.01687	-0.01690
	(0.00289) **	(0.0032) **	(0.0029) **	(0.0033) **
Race	-0.04614	-0.04611	-0.04629	-0.04621
	(0.00454) **	(0.0056) **	(0.0046) **	(0.0052) **
Birthweight	0.05762	0.05759	0.05745	0.05759
	(0.00225) **	(0.0042) **	(0.0023) **	(0.0029) **
Number of siblings	-0.01590	-0.01590	-0.01592	-0.01589
	(0.00135) **	(0.0013) **	(0.0013) **	(0.0014) **
Child's age	0.03779	0.03980	0.03965	0.03961
	(0.00465) **	(0.0047) **	(0.0050) **	(0.0063) **
Constant	4.39550	4.39550	4.39038	4.39308
	(0.07197) **	(0.0792) **	(0.0843) **	(0.0941) **
MSE_{ML}	0.0297	0.0297	0.0297	0.0297
Fraction due to permanent	0.2272	0.2268	0.2270	0.2267

Test dummies not reported. Estimates are almost identical to those in Table 6.
(1) No interaction terms
(2) Includes interactions of inputs with lnAo
(3) Includes interactions of inputs with mother's education. Education is de-meaned before interacting.
(4) Includes interactions with mother's education and lnAo. Education is de-meaned before interacting.
** Significant at 5%; * Significant at 10%

Table 8

Child's skill endowment lnAo
Descriptive Statistics

	lnAo	observed part of lnAo	unobserved part of lnAo
Mean	4.66631	4.66676	-0.00045
Minimum	4.18886	4.44012	-0.31972
Maximum	5.11929	4.93039	0.34099
Standard error	0.11131	0.07497	0.08165
Variance	0.01229	0.00562	0.00667
Fraction of total variance		0.457445	0.542555

Table 9

Initial Wage Equation

	Variable	Parameter	Std. Error
β_{80}	Intercept	0.285278	(0.046167)
β_{83}	age	0.014890	(0.003761)
β_{84}	age^2	0.000075	(0.000075)
β_{85}	education	0.040127	(0.008805)
β_{86}	race	0.187024	(0.021989)
β_{861}	AFQT	0.004514	(0.191204)

Re-employment Wage Equation

	Variable	Parameter	Std. Error
β_{66}	t	-0.002976	(0.000206)
β_{67}	E_t	0.009913	(0.001083)
β_{68}	f_{t-1}	0.053151	(0.008841)
β_{69}	p_{t-1}	0.034901	(0.009376)
β_{70}	E_t * educ	0.000052	(0.001160)
β_{118}	UE	-0.000386	(0.000056)
β_{119}	SWAGE	0.006473	(0.001938)
β_{120}	SERV	0.051242	(0.018417)

Specification with heterogeneity (column (2) in Table 7)
The values of the local demand condition variables (UE, SWAGE, SERV) at the time of the mother's initial wage observation appear in the initial wage equation (with the same coefficients). The time trend *t* is set to the time (in quarters) since the mother's last work period prior to childbirth.

Table 10

Full-Time Probit

	Variable	Parameter	Std. error
β_{01}	Intercept	-17.38835	(0.035315)
β_{1}	age	0.236930	(0.001779)
β_{2}	age^2	-0.006417	(0.000039)
β_{3}	education	0.308073	(0.001470)
β_{4}	race	0.442155	(0.005374)
β_{5}	f_{t-1}	1.957106	(0.021490)
β_{8}	AFQT	0.322740	(0.000627)
β_{110}	E_t	0.060500	(0.002499)
β_{10}	t	0.070124	(0.000675)
β_{89}	UE	0.003781	(0.006883)
β_{90}	SWAGE20	0.273700	(0.084972)
β_{91}	SERV	2.197499	(0.028775)
β_{11}	BW	-0.117509	(0.002067)
β_{12}	gender	-0.609491	(0.003625)
β_{121}	$NSIB_t$	0.000356	(0.002802)
β_{13}	I[age<20]	0.006230	(0.005847)
β_{71}	I[age>33]	-0.552271	(0.013812)
β_{101}	EXPBEF	0.000054	(0.005659)
β_{113}	workbef	0.004854	(0.014623)
β_{7}	C_t	-0.141464	(0.002576)
β_{15}	$I[C_t>0]$	-0.009982	(0.025851)
β_{16}	I[t=1]	0.000175	(0.024201)
β_{17}	I[t<5]	-0.000027	(0.012282)
β_{98}	I^c_{t-1}	-0.035636	(0.068155)
β_{181}	BEN	0.000096	(0.000026)
β_{9}	D_t	0.043932	(0.000789)
β_{182}	I[TLI or DWR]	0.252651	(0.139407)
β_{183}	TL_LENGTH	-0.176754	(0.010957)
β_{185}	I[TL_HIT or WR_HIT]	2.015537	(0.235916)
β_{186}	REMAIN_TL_ELIG	0.354263	(0.017052)
β_{188}	REMAIN_CAT_ELIG	0.001409	(0.000091)
β_{1811}	WR_LENGTH	-0.016405	(0.009260)
β_{1813}	AGE_EXEM	0.000995	(0.001694)
β_{1814}	EXEMP	-0.885236	(0.066734)
β_{1818}	FLAT_DIS	0.061179	(0.000490)
β_{1819}	PERC_DIS	0.128807	(0.002960)
β_{1821}	ENFORCE	0.117756	(0.004298)
β_{1822}	EITC	-0.070353	(0.007620)
β_{19}	CCDF	-0.175724	(0.004420)

Specification with heterogeneity (column (2) in Table 7)

Variables are color coded based on the part of the structural model where they appear: Yellow - mother's wage equation. Green - child ability endowment. Pink - utility function.Blue - welfare benefit rules. There is some overslap (e.g., education, race and AFQT enter both the wage equation and the ability endowment).

Part-time Probit

	Variable	Parameter	Std. error
β_{02}	Intercept	-7.861538	(0.118154)
β_{116}	age	0.117989	(0.007260)
β_{117}	age^2	-0.003215	(0.000170)
β_{20}	education	0.337879	(0.006281)
β_{21}	race	0.230337	(0.029273)
β_{6}	p_{t-1}	1.771106	(0.044958)
β_{23}	AFQT	-0.080644	(0.001411)
β_{111}	E_t	0.054194	(0.007824)
β_{88}	t	0.005698	(0.021040)
β_{92}	UE	0.001896	(0.019339)
β_{93}	SWAGE20	-0.735904	(0.019979)
β_{94}	SERV	1.384997	(0.067386)
β_{25}	BW	0.512115	(0.016102)
β_{26}	gender	0.257402	(0.022183)
β_{122}	$NSIB_t$	-0.001015	(0.013024)
β_{27}	I[age<20]	0.800193	(0.036788)
β_{72}	I[age>33]	-6.738273	(0.057939)
β_{102}	EXPBEF	0.000675	(0.002068)
β_{114}	workbef	0.002678	(0.070693)
β_{22}	C_t	-0.072690	(0.007202)
β_{29}	$I[C_t>0]$	0.498643	(0.082364)
β_{30}	I[t=1]	-1.251982	(0.019873)
β_{31}	I[t<5]	0.002028	(0.056250)
β_{99}	I^c_{t-1}	-0.354102	(0.006412)
β_{321}	BEN	0.002941	(0.000119)
β_{24}	D_t	-0.036316	(0.003505)
β_{322}	I[TLI or DWR]	1.181734	(0.232954)
β_{323}	TL_LENGTH	-0.063936	(0.006909)
β_{325}	I[TL_HIT or WR_HIT]	2.310756	(0.282968)
β_{326}	REMAIN_TL_ELIG	0.193959	(0.012152)
β_{328}	REMAIN_CAT_ELIG	-0.016354	(0.000540)
β_{3211}	WR_LENGTH	-0.371060	(0.011398)
β_{3213}	AGE_EXEM	0.002444	(0.002373)
β_{3214}	EXEMP	0.089808	(0.076026)
β_{3218}	FLAT_DIS	0.169071	(0.000644)
β_{3219}	PERC_DIS	0.339384	(0.010223)
β_{3221}	ENFORCE	0.662682	(0.022656)
β_{3222}	EITC	0.194178	(0.018562)
β_{33}	CCDF	-0.111043	(0.023759)

Specification with heterogeneity (column (2) in Table 7)

Table 11

Childcare Probit

	Variable	Parameter	Std. error
β_{341}	Intercept	-2.744015	(0.263171)
β_{35}	age	0.429771	(0.017690)
β_{36}	age^2	-0.009583	(0.000357)
β_{37}	education	0.062875	(0.003044)
β_{38}	race	0.062124	(0.013632)
β_{39}	f_{t-1}	-0.213544	(0.064352)
β_{40}	p_{t-1}	-0.460165	(0.037726)
β_{42}	AFQT	0.005769	(0.000331)
β_{112}	E_t	0.007387	(0.008834)
β_{44}	t	-0.003138	(0.000489)
β_{95}	UE	-0.003047	(0.003940)
β_{96}	SWAGE20	-0.072581	(0.004545)
β_{97}	SERV	-0.276849	(0.016542)
β_{45}	BW	0.076096	(0.007453)
β_{46}	gender	-0.028140	(0.008817)
β_{123}	$NSIB_t$	-0.000440	(0.004964)
β_{47}	I[age<20]	0.411772	(0.020519)
β_{87}	I[age>33]	0.797243	(0.176605)
β_{103}	EXPBEF	0.001653	(0.001446)
β_{115}	workbef	0.004992	(0.016028)
β_{41}	C_t	0.001756	(0.008590)
β_{49}	$I[C_t>0]$	0.098599	(0.019532)
β_{50}	I[t=1]	0.003646	(0.066120)
β_{51}	I[t<5]	-0.031828	(0.034687)
β_{100}	I^c_{t-1}	1.177289	(0.031967)
β_{521}	BEN	-0.001414	(0.000047)
β_{43}	D_t	-0.011042	(0.001537)
β_{522}	I[TLI or DWR]	0.213688	(0.162023)
β_{523}	TL_LENGTH	0.010261	(0.012367)
β_{525}	I[TL_HIT or WR_HIT]	0.556541	(0.166595)
β_{526}	REMAIN_TL_ELIG	-0.016976	(0.014242)
β_{528}	REMAIN_CAT_ELIG	-0.013165	(0.000677)
β_{5211}	WR_LENGTH	0.030722	(0.008422)
β_{5213}	AGE_EXEM	-0.004698	(0.002427)
β_{5214}	EXEMP	-0.170118	(0.070378)
β_{5218}	FLAT_DIS	-0.000302	(0.000419)
β_{5219}	PERC_DIS	-0.023839	(0.006180)
β_{5221}	ENFORCE	0.126986	(0.010611)
β_{5222}	EITC	0.209939	(0.022456)
β_{53}	CCDF	-0.073595	(0.014738)

Specification with heterogeneity (column (2) in Table 7)

Table 12

Variance Covariance Estimates of the vector of error terms

	ε_f	ε_p	ε_c	ε_s	ε_w
ε_f	1.0000000				
ε_p	-0.5334026	6.7770369			
ε_c	0.0130520	-0.0878713	1.0000000		
ε_s	0.0176224	0.0530314	-0.0023566	0.0296734	
ε_w	0.0007788	-0.0179218	0.0002907	-0.0169229	0.1721507

Specification with heterogeneity (column (2) in Table 7)

Correlation matrix of the vector of error terms

	ε_f	ε_p	ε_c	ε_s	ε_w
ε_f	1.0000000				
ε_p	-0.2048968	1.0000000			
ε_c	0.0130520	-0.0337542	1.0000000		
ε_s	0.1023011	0.1182578	-0.0136804	1.0000000	
ε_w	0.0018770	-0.0165924	0.0007007	-0.2367748	1.0000000

Specification with heterogeneity (column (2) in Table 7)

Covariance matrix of the permanent components μ_k

	μ_f	μ_p	μ_c	μ_s	μ_w
μ_f	0.8171407				
μ_p	-0.5334026	2.0039500			
μ_c	0.0130520	-0.0878713	0.0041639		
μ_s	0.0176224	0.0530314	-0.0023566	0.0067301	
μ_w	0.0007788	-0.0179218	0.0002907	-0.0169229	0.0884818

Specification with heterogeneity (column (2) in Table 7)

Correlation matrix of the permanent components μ_k

	μ_f	μ_p	μ_c	μ_s	μ_w
μ_f	1.0000000				
μ_p	-0.4168341	1.0000000			
μ_c	0.2237566	-0.9619470	1.0000000		
μ_s	0.2376328	0.4566470	-0.4451643	1.0000000	
μ_w	0.0028962	-0.0425610	0.0151472	-0.6934854	1.0000000

Specification with heterogeneity (column (2) in Table 7)

Covariance matrix of the transitory components v_k

	v_f	v_p	v_c	v_s	v_w
v_f	0.1828593				
v_p	0.0000000	4.7730869			
v_c	0.0000000	0.0000000	0.9958361		
v_s	0.0000000	0.0000000	0.0000000	0.0229434	
v_w	0.0000000	0.0000000	0.0000000	0.0000000	0.0836689

Specification with heterogeneity (column (2) in Table 7)

Table 13

Chi-squared Goodness-of-fit Tests of the Within-Sample Choice Distributions

			CHOICE			
Qtr.	Home & no child care	Full-time & child care	Part-time & child care	Home & child care	Row	
1	0.16	0.82	0.01	0.06	1.04	
2	0.05	0.80	0.00	0.21	1.06	
3	0.51	0.03	1.02	0.07	1.63	
4	0.12	2.06	0.37	0.25	2.79	
5	1.59	1.50	0.48	0.19	3.75	
6	0.21	0.00	0.47	0.03	0.71	
7	0.12	0.00	0.80	2.42	3.34	
8	0.43	0.02	0.06	0.62	1.12	
9	0.99	0.24	0.08	7.96	9.28	*
10	0.83	0.00	0.09	4.15	5.07	
11	0.86	0.65	0.00	7.60	9.11	*
12	0.98	0.16	0.49	3.87	5.50	
13	1.04	0.08	1.57	0.75	3.43	
14	0.01	0.08	0.00	0.29	0.38	
15	0.40	0.01	0.23	2.12	2.76	
16	0.56	0.01	0.01	1.57	2.16	

* Statistically significant at 0.05 (Critical Value=7.82)

Table 14

Fit to Test Scores and Initial Wages

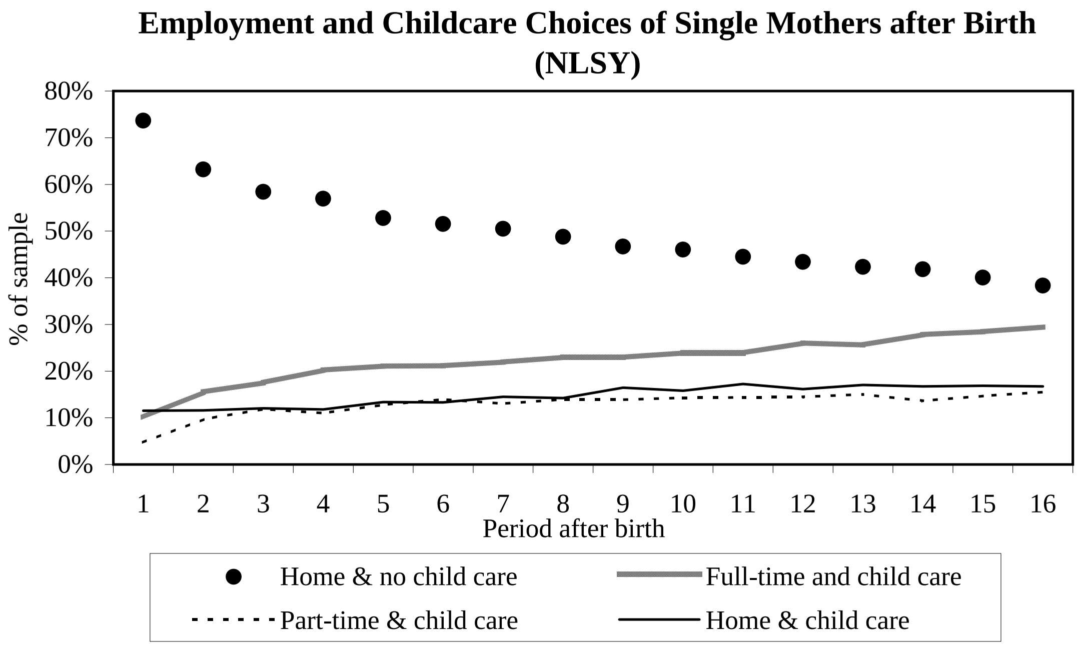
Log(test score)

	PPVT			PIAT - Math		PIAT-Reading	
Child's Age	3	4	5	5	6	5	6
Actual	4.367	4.269	4.402	4.539	4.543	4.633	4.606
	(0.191)	(0.295)	(0.239)	(0.152)	(0.128)	(0.152)	(0.095)
Predicted	4.318	4.357	4.369	4.540	4.545	4.597	4.604
	(0.189)	(0.196)	(0.187)	(0.184)	(0.191)	(0.182)	(0.190)

Log(Initial Wages)

	Actual	Predicted
Total average	1.3760	1.3662
< High school	1.3142	1.3245
> High school	1.5782	1.5707
30 years old +	1.5649	1.6023
< 30 years old	1.3462	1.3440
Black/Hispanic	1.4049	1.3869
White	1.2622	1.2694

Figure 1

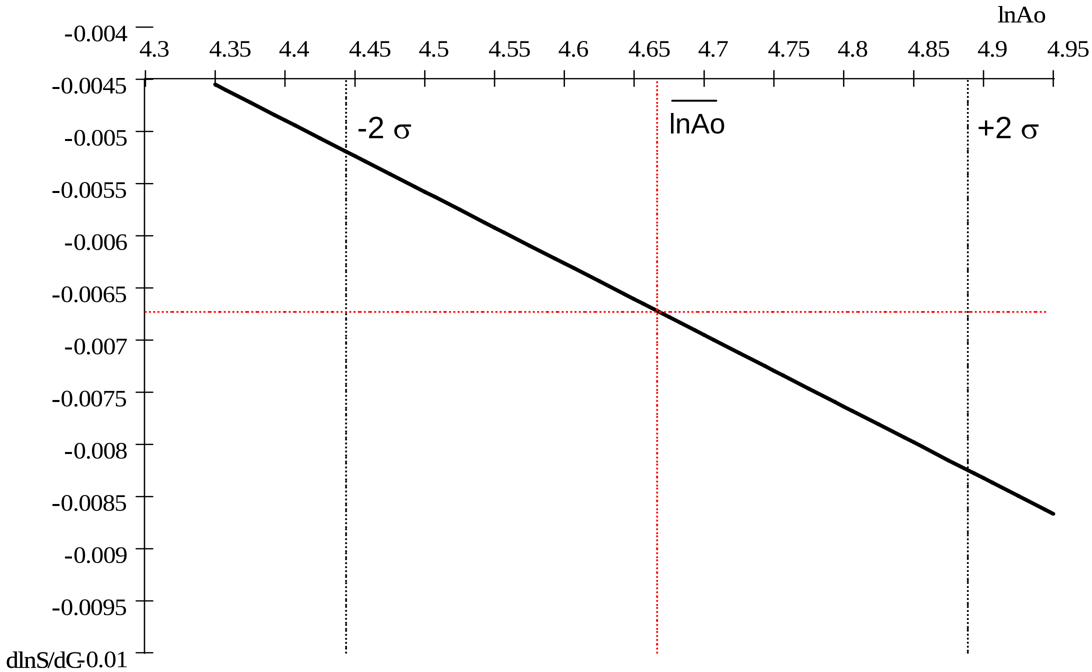


Note: The first 12 periods correspond to quarters (3-months) and the last four correspond to semesters.

Figure 2

Effect of Child Care Use on Cognitive Ability

$$dlnS_t/dC_t=0.02529-0.00686lnA_o$$



Effect of log (Cumulative Income) on Cognitive Ability

$$dlnS_t/dlnI_t=0.01159+0.001703lnA_o$$

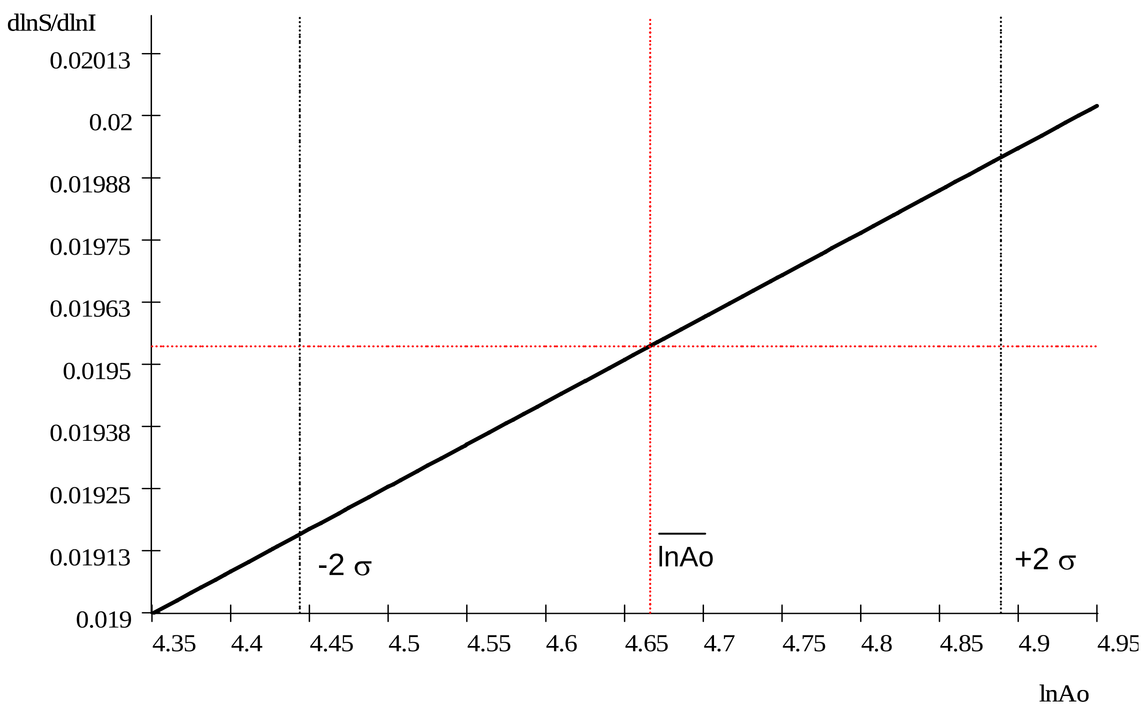


Figure 3

Model Fit to Choice Distributions

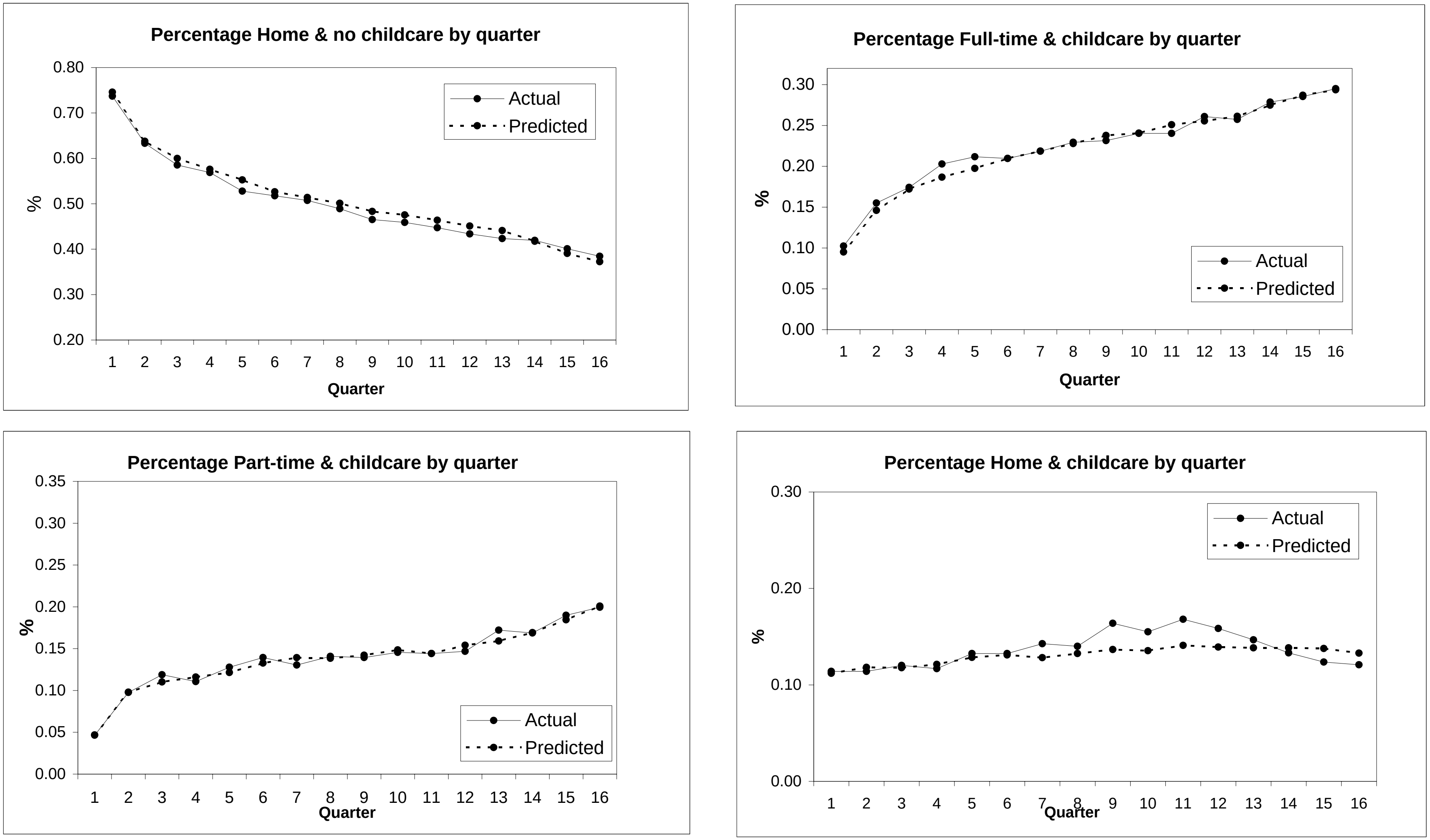
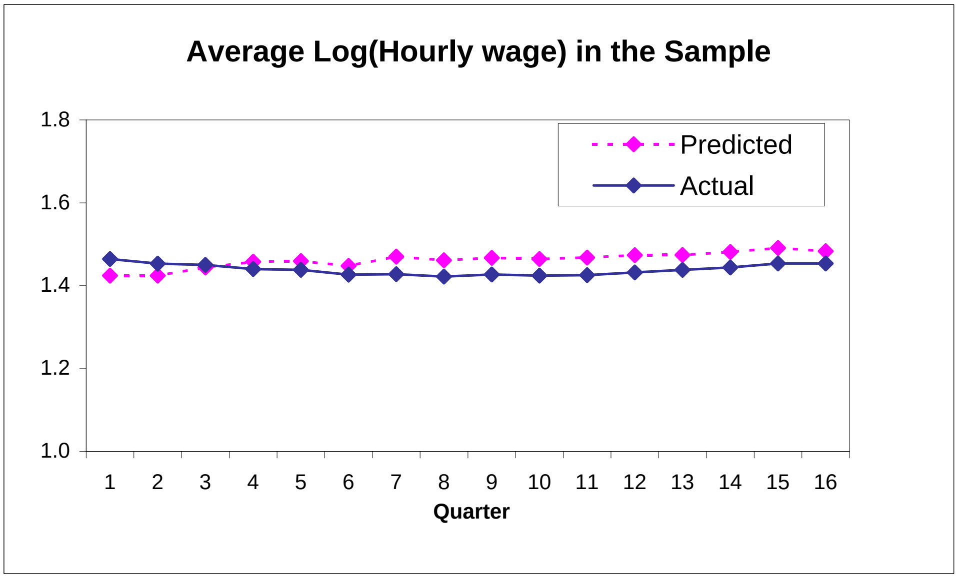
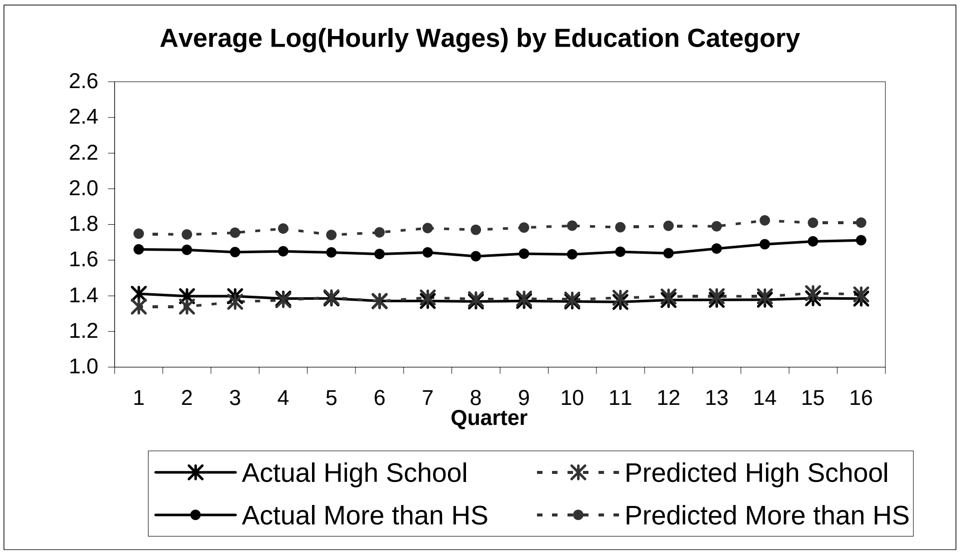


Figure 4


Average Log(Hourly wage) in the Sample
Predicted
Actual
1.8
1.6
1.4
1.2
1.0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Quarter


Average Log(Hourly Wages) by Education Category
2.6
2.4
2.2
2.0
1.8
1.6
1.4
1.2
1.0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Quarter
Actual High School
Predicted High School
Actual More than HS
Predicted More than HS

Appendix 1

Probit to predict child care choices of non-working women in years 4 and 5 after childbirth

Dependent Variable-> Pr(using child care in *t*)		
Whether worked before giving birth	0.592015	
	(0.2078)	**
(Whether worked before) x (Avg. wage before)	-0.06419	
	(0.0398)	*
Total work experience (prior to giving birth)	-0.005986	
	(0.0194)	
Child's race	-0.08744	
	(0.1702)	
Child's gender	0.049666	
	(0.1196)	
Mother's education	0.082132	
	(0.0384)	**
Total work experience since child birth	-0.398349	
	(0.0698)	**
Total child care use since child birth	0.222627	
	(0.0527)	**
Whether used child care or not in *t-1*	1.780094	
	(0.1639)	**
Estimation	Probit	
Number of observations	867	
Pseudo-R^2	0.4585	

*Additional controls: Marital status at child birth (never married, separated,divorced, widowed),urban/rural residence and mother's age at birth.

**For women who reported working full-time in a given period after the third year, we imputed a child care value equal to 1; if the mother reported working part-time, we imputed a child care value equal to 0.5. Finally, if the mother does not work in a given period, we imputed a child care value of 0.5 if thepredicted probability of child care use based on this model exceeds 0.65.We choose this threshold to obtain a smooth trend of child care use since childbirth and until the end of the fifth year.

Appendix 2

Cognitive Ability Tests in our NLSY sample

Descriptive Statistics

	PPVT			PIAT - Math		PIAT-Reading	
Child's Age	3	4	5	5	6	5	6
Sample (N=1,464)	80.263	74.334	83.767	94.719	94.802	104.089	100.585
	(14.952)	(19.512)	(17.504)	(14.329)	(11.727)	(15.319)	(9.462)
Non-whites	78.007	70.836	82.135	93.836	94.247	103.358	100.482
	(14.169)	(17.958)	(16.889)	(14.289)	(11.685)	(15.454)	(9.269)
Whites	92.167	89.299	93.852	99.576	97.657	108.100	101.112
	(13.348)	(18.885)	(18.001)	(13.634)	(11.578)	(13.970)	(10.422)
Maternal education (12 yrs+)	82.820	78.748	88.743	97.084	96.823	106.755	102.265
	(14.369)	(18.917)	(17.648)	(14.178)	(11.663)	(15.131)	(9.425)
Maternal education (<12 yrs)	76.301	68.748	79.508	91.767	92.751	100.697	98.847
	(15.025)	(18.847)	(16.245)	(13.991)	(11.449)	(14.909)	(9.197)
Male	79.753	72.242	83.035	93.726	93.710	102.557	99.232
	(14.664)	(20.048)	(18.143)	(14.307)	(12.292)	(15.563)	(9.404)
Female	80.707	76.299	84.569	95.739	95.827	105.685	101.838
	(15.225)	(18.820)	(16.783)	(14.305)	(11.091)	(14.922)	(9.357)

PPVT: Peabody Picture Vocabulary Test

PIAT: Peabody Individual Achievement Test

Appendix 3

Average Test Scores for Children born prior to 1990 by State characteristics

	Average	St. Dev	ttest
States that implemented TL waivers	93.34	(1.82)	-0.46
States that did not implement TL waivers	92.42	(1.08)	
States that implemented WR waivers	89.77	(1.35)	1.56
States that did not implement WR waivers	93.45	(1.09)	
States with TL lower than 3 years	90.2	(2.46)	0.87
States with TL higher than 3 years	93.02	(1.00)	
States with immediate WRs	93.48	(1.81)	-0.66
States with WRs of at least 1 month	92.20	(0.95)	
States with Age of Youngest child exemption < 6 months	93.40	(2.20)	-0.51
States with Age of Youngest child exemption > 6 months	92.38	(0.84)	

Source: NLSY, sample of single mothers