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

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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.

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1. Introduction

Effects of home inputs on child cognitive development have been widely analyzed, especially in the psychology and sociology literatures. Much prior work has focused on effects of maternal time vs. alternative provider time, and 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 labor market outcomes in later life (e.g., wages, employment) are largely determined by skill "endowments" 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 shows that early cognitive achievement is a strong predictor of later life outcomes – e.g., high early achievers tend to have higher educational attainment and higher earnings; and are less likely to have teenage births, be on welfare or participate in crime. Bernal and Keane (2007) 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] Thus, understanding the determinants of early cognitive achievement may be critical for design of public policy aimed at improving subsequent labor market outcomes (see Cunha et al (2006)). However, the question of what determines child cognitive achievement in general, and the role of parental time and goods inputs in particular, remains largely unresolved.

Two key problems hamper research in this area: (1) a paucity of good data on inputs into child cognitive development, and (2) the difficult selection problem arising 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 effects 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.

In studying effects 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

[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.

work/daycare. To illustrate problem (1), suppose that high-skilled women are more likely to have high cognitive ability children, and more likely to work/use day care. Then, a statistical analysis may find a spurious positive effect of maternal employment/child care use on cognitive outcomes. To illustrate (2), suppose mothers of low ability endowment children compensate by spending more time with them, and thus tend to work less. Again, the estimated effect of maternal employment/child care on child cognitive outcomes is upwardly biased. Clearly, these selection issues make evaluating 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. 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]

This discussion gives an intuition for our approach, but 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. But this over-simplifies the approach we actually take. As Rosenzweig and Wolpin (2000) stress, what IV estimates depends on what one controls for. For example, welfare reform may have altered goods inputs, not just time inputs. Thus, to interpret our estimates, we must (i) adopt a particular theoretical model, including specification of a child cognitive ability production function, and (ii) consider how this relates to the outcome equation we actually estimate (i.e., not all production function inputs are

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[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 suggests there was point in time when welfare rules simply became stricter. But this is an over-simplification 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 and nature of welfare rule changes. See, e.g., Fang and Keane (2004) for an extensive discussion.

observed due to data limitations, complicating interpretation. We discuss this in section 4.1).

Hence, our empirical work is guided by a structural model of mothers' employment and childcare decisions described in section 4.1. Using this model, we obtain approximate decision rules for employment and child care use, and estimate these jointly with a child cognitive ability production function and mother's wage function – an approach we call "quasi-structural." In our selection model, welfare rules provide natural exclusion restrictions, as it is plausible they enter decision rules for employment and daycare use, but not the 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 year of full-time work and daycare use reduces child cognitive ability test score by roughly 2.7% on average, or 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 a quasi-structural approach over linear IV is we can accommodate unobserved heterogeneity in effects of maternal work and childcare use on child outcomes. We find evidence of substantial observed and unobserved heterogeneity in daycare effects. Negative effects are larger for better-educated mothers and children with higher skill endowments.

Another advantage is that, by estimating the work and childcare decision rules, wage function and production function as a <u>system</u>, 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 the 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 in the four equation system may lead

[5] Using linear IV, the coefficient on quarters of childcare is -.00807 with a standard error of .00333 (t = -2.42). For a version of the quasi-structural model with homogeneous childcare effects the coefficient is -.00698, with a standard error of .00045 (t=15.5).

to inconsistency.[6] Another advantage of single equation IV is its relative simplicity of implementation, which, in Bernal and Keane (2007) enables us to examine a large number of alternative specifications of the child cognitive ability production function.[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/daycare 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 cannot avoid making assumptions (either explicitly or implicitly) about expectations.[9]

Our study of single mothers extends earlier work by Bernal (2007) 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 1.8% reduction in child cognitive ability test scores. A key motivation of our work was to see if that result generalizes from married to single mothers. Our estimate for single mothers is larger (2.7%), but the similarity of the results is still striking.

Bernal (2007) relied on very different exclusion restrictions from those used here. She treats age profiles of husband and wife earnings as exogenous, in that: (1) only parents' skill endowments, and not their age, affect the skill the child inherits, and (2) only skill endowments

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[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] E.g., it may be cumulative inputs that matter, analogous to the 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 more. Or, different types of day care, such as formal vs. informal, may differentially affect 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 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.

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 investment in children. Thus, otherwise identical women who have children when they or their husbands are at different points in the life-cycle will have different incentives to work. This creates exogenous variation in work/childcare use that helps identify effects of maternal time inputs.[10] We find this approach appealing, but exogeneity of the welfare policy rules used here seems less subject to challenge.

Aside from the advantage of having highly plausible instruments (i.e., welfare rules), the study of single mothers is also of special policy interest, given that welfare policy changes have substantially increased their work and daycare usage in recent years. If daycare has negative effects on the test scores of their children it suggests an additional cost of these policies that should be considered when evaluating their overall success.

2. Literature Review

Many prior studies, mostly in developmental psychology, use the NLSY to assess effects of maternal employment or childcare on child cognitive development. For reviews see Haveman and Wolf (1994), Lamb (1996), Love et al (1996), Blau (1999), Ruhm (2002), Bernal and Keane (2007). Most studies present simple correlations of inputs and child outcomes, not controlling for family or child characteristics. Rarely are controls for selection bias implemented.[11]

The results of the prior literature are quite inconclusive. Of the papers that use the NLSY to assess effects 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]

[10] In the NLSY data Bernal (2007) 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).

[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/specification of cognitive ability production functions, and raise many of the issues raised here. We focus on specific issues that arise in estimating effects of parental time, child care and goods inputs on child development.

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 a cognitive outcome for child *i* of mother *j* at age *t* (e.g., a test score). T_{ijt} is a measure of maternal time inputs up through age *t*. It 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. It may include variables such as mother's age, education, IQ, etc. (to capture inherited ability), 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 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.

While (1) is the general setup that, at least implicitly, underlies most papers in the literature, none actually estimate this equation and many depart from it greatly. One fundamental problem is that the maternal time input *T* and goods inputs *G* are not directly observed. Most papers ignore this problem, simply using maternal employment or childcare use in place of maternal time. And most use only one of these variables, rather than examining both.[13] Similarly, most papers simply ignore *G*.[14] A few proxy for it using household income or the NLSY's "HOME" environment index. The later is problematic as it is 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 and a child ability production function, by noting the difficulty in interpreting estimates when proxies are used for maternal time and goods inputs.

Second, most papers include only current inputs. This is a strong assumption, especially as the human capital literature has emphasized cumulative inputs. Of course, in a more general specification the whole history of inputs since birth may matter for time *t* outcomes. Few papers discuss their assumptions regarding timing of inputs.[15] We discuss these issues in Section 4.

[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)).

Finally, most papers estimate equation (1) by OLS, ignoring potential endogeneity of the inputs – i.e., correlation of maternal work and daycare use decisions, and goods inputs, with the unobserved ability endowments, μ_j and δ_{ij}. A few recent studies try 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 (FE), or "value added" models, and/or (3) instrumental variables.

Consider first studies that use extensive controls, such as Baydar and Brooks-Gunn (1991), Vandell and Ramanan (1992), Parcel and Menaghan (1994), Han et al (2001) and Ruhm (2002). They control for many observed characteristics of the mother and child, including the mother's AFQT score - a measure of IQ available in the NLSY. But they still obtain inconclusive results. For example, Baydar and Brooks-Gunn (1991) find maternal work during the child's first year negatively affects cognitive outcomes, while Vandell and Ramanan (1992) report positive effects of early employment on math scores, and 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 employment on 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 child outcomes. They analyzed 2402 low-income families during the recent welfare reform, and found those mothers' transitions off welfare and into employment were 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 welfare rules as instruments for maternal employment as we do here.

James-Burdumy (2005) estimated household FE models on 498 siblings from the NLSY. She finds the effect of maternal employment varies by the cognitive assessment used and the timing of employment.[16] By taking sibling differences, one eliminates the mother fixed effects μ_j from (1), but <u>not</u> the child fixed effects δ_{ij}. If mothers make time compensations for children depending on their ability type, a household fixed effect model is not appropriate, as maternal employment is correlated with the child specific part of the cognitive ability endowment. The FE estimator also 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.

[16] According to the FE estimates in her Table 5, an increase in maternal work from 0 to 2000 hours in year 1 of a 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 (-2.7%). But she finds no significant effect of maternal work after the first year, so her estimate of the effect of five years of full-time employment is much smaller than ours.

Blau (1999) and Duncan-NICHD (2003) study effects of childcare use and childcare quality on child outcomes. They use similar methodologies, including a wide range of proxies for the child ability endowment (like mother's AFQT and education), controls for many aspects of the home environment, and use of FE and value added specifications.[17] The main difference is that Blau uses the NLSY while Duncan uses the NICHD Study of Early Child Care. Blau (1999) concludes "child care inputs … during the first three years of life have little impact on … child outcomes …" while Duncan finds a modest positive effect of improved childcare quality.[18]

For our purposes, a difficulty arises in interpreting the Blau and Duncan results, because they control for *G* using the HOME environment index. This combines survey items measuring both goods inputs (e.g., books in the home) and time inputs (e.g., how often the child is read to, eats meals with parents, etc.). Thus, the coefficients on maternal work and daycare use will measure effects 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 – including how a decline in the time input (due to increased work/daycare use) affects time spent reading to the child and so on.

Blau (1999) and Duncan-NICHD (2003) also contain useful discussions of the limitations of FE and value added specifications. As they point out, neither provides a panacea for dealing with unobserved child ability, as both rely on assumptions that are in some ways stronger than OLS. For example, the household FE estimator requires that input choices be unresponsive to the child specific 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.[19] Neither approach, nor child fixed effects, deals with the endogeneity problem that arises because current inputs may respond to lagged test scores. One way to approach to this problem is linear IV.

Only two papers have attempted to use IV – Blau and Grossberg (1992) and James-Burdumy (2005). Both look at effects of maternal work on child outcomes, and do not examine daycare effects *per se*. More importantly, both papers use extremely weak instruments. As a result, the standard errors on the maternal work variables in their 2SLS regression are so large that no plausibly sized effect could possibly be significant (i.e., in each case, to attain 5%

[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.
[18] In particular, a one-standard deviation in childcare 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.

significance, maternal work over a three year period would have to change a child's tests scores by roughly 50 points or 3 standard deviations).[20] Thus, we would argue that their attempts to implement IV were not successful.

In contrast, the welfare policy and local demand instruments we employ are much stronger. Indeed, in Bernal and Keane (2007), where we implement an IV approach, we note that first stage marginal R^2 values obtained using these instruments (i.e., about .09) are fairly large relative to what one typically sees in the IV literature, and, in the second stage, standard errors on maternal work and daycare use do not "explode" when these instruments are used.

Finally, Bernal (2007) estimates a structural model of work and childcare decisions of married women after childbirth. Estimating the cognitive ability production function jointly with mothers' decision rules adjusts for the selection arising because certain types of children are more likely to be in childcare and/or have working mothers. Her results suggest an additional year of full-time work and childcare reduces test scores by about 1.8% (at ages 3 through 7).

But, as we noted earlier, Bernal 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 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 arising because children placed in daycare may differ systematically from those who are not, we use welfare policy rules as instruments (or exclusion restrictions) to help identify our selection model. Welfare rules have a large impact on labor supply of single mothers (see Moffitt (1992)). To construct our instruments, we collected very detailed information on State welfare policies. The working paper version contains a detailed list of sources, and more detail on construction of the instruments. Here, we briefly highlight the key aspects of Section 1115 welfare waivers and the 1996 Welfare Reform (PWRORA) relevant to this work. Table 1 presents the complete instrument list, including all policy variables. Each

[20] For Blau and Grossberg (1992), who use work experience prior to childbirth to instrument for maternal employment, compare columns 1 and 2 of their Table 2. For James-Burdumy (2005), who uses the percentage of the county labor force employed in services to instrument for maternal employment, compare columns FE and IV-FE from her Table 3. Note that, in the case of Blau and Brossberg (1992), it is also questionable if work prior to childbirth is uncorrelated with the child ability endowment (as it is likely correlated with mother's ability).

instrument has up to three subscripts: *i* for individual, *s* for State and *t* for period (quarter).

3.1. Benefit Termination Time Limits

Under AFDC, single mothers with children under 18 were *entitled* to benefits, provided they met the income and asset screens. But under Section 1115 Waivers and TANF, 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 lets States set shorter limits (e.g., California imposes a 5-year limit, while Texas and Florida impose 2 to 3 year limits).

Time limits have both direct and indirect effects. The direct effect is straightforward (i.e., when a woman hits the time limit she becomes ineligible). The indirect effect is subtler: forward-looking individuals should try to "bank" months of eligibility for later use. In the instrument list we include five variables to capture these two effects of time limits (see Table 1). We include, e.g., a dummy for whether a single mother's State of residence had imposed a time limit (TLI_{st}) at time *t*, a dummy for whether the time limit could possibly be binding (TL_HIT_{ist}), and the maximum potential remaining time before hitting the time limit ($REMAIN\_TL\_ELIG_{\mathrm{ist}}$). Note that we incorporate both time limits created under TANF and earlier under AFDC waivers.

We made a great effort to construct person specific instruments. For example, consider TL_HIT_{ist}. Say a woman resides in a State that imposed a 5-year time limit 6 years earlier. Then it is possible she could have hit the limit, provided her oldest child is at least 5. If her oldest child is less than 5, she cannot have participated in AFDC/TANF for 5 years, and so cannot have hit the limit. Thus, using data on ages of children, we can tailor the instrument to individual cases. Crucially, we do not use actual welfare participation histories to determine a woman's remaining eligibility, as participation is endogenous. We assume welfare rules and demographics (like ages and numbers of children) are exogenous (given controls for mother characteristics), so 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 time costs of welfare participation. Under TANF, recipients must commence "work activities" within two years of coming on assistance to maintain benefits. But many States adopted shorter work requirement time limit clocks. Due to variation in when States implemented TANF, and in the length of their clocks, there is substantial variation across States in how early single mothers could have hit binding work requirements. Also, States have the option to exempt single parents with children up to 1 year of age from work requirements, and to provide other exemptions as well. Thus, even within a State, there is variation across women in whether work requirements can be binding, based on age of the youngest child.

We construct five variables to measure work requirements (see Table 1). For example, WR_HIT_{ist}, is a dummy for whether a woman could be subject to work requirements (based on her age, length of the time limit, time since the requirement was implemented, ages of children, etc.), and $AGE\_CHILD\_EXEM_{st}$ is the young child exemption age in State *s* at time *t*.

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

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

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. That is, if a recipient started work, then, for a limited time, a fraction of earnings would be exempt from the BRR. The disregard consisted of a "flat" part (e.g., the first $30 of monthly earnings) and a "percentage" part (e.g., one-third of additional earnings). Both were eliminated after several months.

Starting in late 1992, many States obtained waivers to increase disregards. Under PRWORA, States may set their own disregard levels, and much heterogeneity has emerged. A few States expanded disregards and let them apply indefinitely. We code BRR and the percent disregard together in $PERC\_DISREGARD_{st}$. 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.[22] The Child Support Enforcement (CSE) program, enacted in 1975, pursues efforts to locate absent fathers and establish paternity. CSE expenditures greatly increased from $2.9 billion in 1996 to $5.1 billion in 2002. We use these expenditures as an indicator of child support

[21] The BLS computes the CPI for 24 metropolitan areas and for four regions (west, south, midwest and northeast).
[22] In 2002, child support accounted for approximately 6.5% of single mother's real incomes (March CPS).

enforcement efforts. Specifically, we 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 childcare programs for low-income families. States have considerable autonomy, so a great deal of heterogeneity in program design has emerged. As an additional instrument, we use the State CCDF expenditure per single mother ($CCDF_{st}$) to capture the availability and generosity of child care subsidies in a State.[23]

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

The EITC, enacted in 1975, is a refundable Federal tax credit to supplement wages of low-income families. It was initially a minor program, but a major expansion in 1994-96 created a sizable wage subsidy. Earnings are supplemented at a "phase-in" rate until a ceiling is reached. In 2003 this rate was 34% for a family with one child, and 17 States supplement the federal credit. To account for work incentives created by EITC, we construct the EITC phase-in rate ($EITC_{ist}$) using Federal and State EITC rules together with the mother's family composition.

Finally, we use as instruments three variables that measure local demand conditions: 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 Structural and Quasi-Structural Models

We first present a structural model of single mother's decisions about work and daycare use, and how these affect child outcomes. Rather than presenting a *general* model, we detail a *specific* model we might actually estimate, given available data and computational limitations. This helps clarify the type of assumptions needed to solve and estimate such a model. Next, we describe a "quasi-structural" approximation to the model. This clarifies how some assumptions required for structural estimation can be sidestepped in estimating an approximation. However, as noted earlier, implicit assumptions in these areas still influence the interpretation of results.

4.1. Overview of the Structural Model

Consider a woman making choices about work, childcare and welfare participation in each period t following the birth of a child, 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

[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.

decisions (although we allow for multiple children in the empirical work). In our model the time period is a quarter. 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 childcare is infeasible, there 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, her choice set will vary (e.g., a woman residing in a State with a 36 month welfare time limit won't have the option to receive welfare beyond 36 months). 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 is work status (2=full-time, 1=part-time, 0=no work), g_t is a dummy for welfare participation, and I_t^c is a dummy for use of childcare. 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 is also 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 (2007), a reasonable functional form would be:

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

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 (2) is CRRA in consumption, with parameter α_1. Parameter α_2 is disutility from work. A_t is child cognitive ability; generated by a production function we define below. Mothers get utility from A_t according to a CRRA function with parameter λ, as in Bernal (2007). She estimated λ<1, implying diminishing marginal utility from child ability. Then, mothers have an incentive to use time and goods to compensate children with 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 terms α_5 through α_9 in (2) capture various aspects of the utility/disutility from child-care use. These follow from Bernal (2007), who found they are necessary to fit data on child care utilization well.[24] Parameter α_5 is a 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 search time in finding a daycare center, and/or the psychic cost of first time separation from the child. 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). These parameters capture the fact that: (i) it is more difficult to find day care centers that take infants, (ii) infant care is generally more expensive, and (iii) 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 childcare use may depend on whether childcare 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.[25] 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, as 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 much of the variation away from those figures is likely to be measurement error. The next term in the budget constraint, N_t, is non-labor income, which may include child support payments.

The third term (3) is $B(w_t, h_t, N_t, D_t, R_{st})$, the welfare benefit rule, which determines the benefit a woman receives if she participates in welfare (i.e., 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 rule parameters R_{st}.[26] One such parameter is the grant

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

level a woman with no income receives. This differed greatly across States and time even under AFDC. Under TANF and waivers, substantial heterogeneity across States has also emerged in the rate at which benefits are reduced if a woman has earned or unearned income. Duration of prior welfare participation also matters for benefits, as some States eliminate or reduce the benefit by a 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 childcare 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.

Besides the budget constraint, a woman faces two other constraints that influence work and childcare decisions: a wage function and the child cognitive ability production function. To explain these, it is useful to define w_o as a woman's "initial wage," prior to giving birth. This is the observed wage for an employed woman, or a latent offer wage for non-workers. We model the initial wage as a function of a woman's observed and unobserved characteristics 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, μ_w represents *unobserved* heterogeneity in mothers' skill endowments. The variables education (*educ*), *race* (an indicator for non-white), and *AFQT* capture *observed* heterogeneity in the skill endowment, while *age* (i.e., 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 a woman's State of residence, and $\overline{\theta}_6$ is the associated parameter vector. 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 $v_{w0} \sim \mathrm{N}(0, \sigma_w^2)$.

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, and $\delta \cdot t$ captures the percentage depreciation of a woman's offer wage if she leaves the labor force for t periods after childbirth. Acquiring work experience counteracts 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 a woman worked full-time or part-time in the 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 associated parameter vector. Finally, v_{wt} is a stochastic term due to transitory shocks to productivity and/or measurement error. Again, FIML would require 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 a child is born with a cognitive ability endowment A_o. This endowment is correlated with a set of observable variables, and also contains an unobservable component, as follows:

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

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, part of the endowment is correlated with observed child characteristics, although the only such observables we have are birth weight (*BW*) and *gender*.

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. Indeed, we find below that age is completely insignificant in the production function.[27]

[27] If age mattered in the production function, and we did not control for it, it would call into question the validity of our welfare policy instruments. These policy rules are correlated with mother's age at childbirth, because the

We emphasize that the coefficients γ_1 through γ_{11} in (5) do not capture causality, 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 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.[28] Dropping the mother and child subscripts, we write:

$$\ln A_t(\mu_s) = \ln A_o(\mu_s) + \gamma_{11}\hat{T}_t + \gamma_{12}\hat{C}_t + \gamma_{13}\ln\hat{G}_t \tag{6}$$

Here, $\hat{T}_t$ denotes the cumulative input of maternal time through age t, $\hat{C}_t$ denotes cumulative input of alternative caregivers' time, and $\hat{G}_t$ denotes cumulative input of goods. It is convenient to let goods enter in log form, for reasons that will become clear shortly. Comparing (1) with (6), the term $\alpha_4 X_t + \mu + \delta$ (i.e., the ability endowment) has been subsumed in ln $A_o(\mu_s)$. And we drop ε because the dependent variable in (6) is actual ability rather than a noisy measurement. In (6) we assume homogeneous coefficients on 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.

As T and G are not directly observed, we need assumptions relating them to observables to obtain an estimable equation. First consider 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.,

teenage mothers in the NLSY79 cohort had children at too early a date to be affected by TANF or waivers. For evidence on the effect of maternal age on child outcomes, see, e.g., Lopez (2003), Geronimus et al (1994) and Bernal and Keane (2007).

[28] A general functional form, where inputs at age t may differentially effect ability at each age t', and μ_s may have different effects 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, and (ii) the effect of the permanent unobservable is constant over time. Similarly, in a typical Mincer earnings function, only cumulative education and experience affect human capital, and the unobserved skill endowment has a constant effect on log earnings.

children's time is divided between daycare, "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),[29] we simply side-step the issue by assuming $T_{it} = T\text{-}C_{it}$, where T is total time in a period. Thus, we distinguish between only two types of time – time with the mother and time in childcare). Then we can rewrite (6) as:

$$\ln A_t(\mu_s) = \ln A_o(\mu_s) + (\gamma_{11}T)\cdot t + (\gamma_{12} - \gamma_{11})\widehat{C}_t + \gamma_{13}\ln \widehat{G}_t \tag{7}$$

where $T{\cdot}t$ and $\widehat{C}_t$ arise from adding $T\text{-}C_{it}$ over t periods. 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 goods input G, which is also largely 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 appreciate the implications of this, suppose 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:

$$\ln \widehat{G}_{it} = \pi_0 + \pi_1 X_i + \pi_2 \mu_{si} + \pi_3 \widehat{C}_{it} + \pi_4 \ln \widehat{I}_{it}(W, H; R) + \pi_5 t + \varepsilon_{it}^{g}\,. \tag{8}$$

This is a conditional decision rule, obtained as the second stage in an optimization process, where, in stage one, a mother chooses childcare inputs and hours of market work. The notation $\widehat{I}_{it}(W, H; R)$ highlights the dependence of cumulative income on histories of wages W, market work hours H, and welfare rules R 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) mothers' decisions about goods inputs may be influenced by (i.e., made jointly with) decisions about work and childcare, and (ii) inputs depend on a mother's characteristics X, such as education, and on the child ability endowment μ_{si}. The time trend in (8) captures growth of cumulative inputs over time. The stochastic term, ε_{it}^{g}, captures mothers' idiosyncratic tastes for investment in the form of goods.[30]

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

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[29] The NLSY's "HOME" environment index contains such variables as how often the child is read to, eats meals with the parents, etc., but it is not sufficiently comprehensive to measure the total maternal quality time input.
[30] This may arise due to heterogeneous preferences for child quality.

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

Equation (9) is estimable, as all independent variables are observable. However, we must be careful about the appropriate estimation method and interpretation of results. As we have stressed, childcare use may be correlated with the unobserved part of a child's ability endowment μ_s. It may also be correlated with ε^g, the mother's taste for goods investment (i.e., if these tastes are correlated with tastes for childcare use, as seems plausible).[31] Thus, for welfare rules R_{st} and local demand conditions τ_{st} to be valid instruments for estimating (9), they must be uncorrelated with both μ_s and ε^g, which we view as a plausible exogeneity assumption.[32]

Cumulative income may also be endogenous in (9), for multiple reasons. First, income depends on the jointly made childcare and work decisions. Hence it is potentially correlated with child ability for the same reasons as are operative for childcare use. Second, income depends on the mother's wage rate, which depends on her unobserved ability endowment. If this is correlated with the child ability endowment (i.e., $\rho \neq 0$ in (5)), it also generates correlation between income and μ_s. Thus, we need to instrument for income as well. Again, we argue that the welfare rules R_{st} and local demand conditions τ_{st} provide plausible instruments, as they have important effects on work decisions, yet it is plausible that they are uncorrelated with child ability endowments.

Even assuming we obtain consistent estimates of (9), it is still important to recognize that the childcare "effect" we estimate is $\beta_2 = \gamma_{12} - \gamma_{11} + \gamma_{13} \cdot \pi_3$. This is the effect of childcare 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 childcare subsidy would affect child outcomes. Such subsidies would not only alter day care use, but also the budget constraint conditional on I_{it}, and I_{it}^c, and hence the decision rule for goods

[31] For instance, a mother with a high taste for child quality may both spend more time with the child (i.e., use less daycare) and invest more in the child in the form of goods. This would tend to bias estimated effects of daycare in a negative direction, since not only the maternal time input but also the goods input is lower for children in daycare.

[32] 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> μ_s and the mother's tastes for goods investment in the child, ε^g.

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 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 childcare, 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.[33] Bernal (2007) found that returns to maternal time in production of child cognitive ability are greater for children with higher initial skill endowments.

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 $v_{st} \sim \mathrm{N}(0,\sigma_v^2)$.[34]

In describing the structural model, we have ignored fertility, and assumed a mother has just one child. With multiple children, one must specify how maternal contact time is allocated among them, and take a stand on whether maternal time is a "public good." Thus, structurally modeling families with multiple children is difficult. In either an IV or quasi-structural approach, we can sidestep these issues by including the number of children in the test score equation, and interacting it with the other inputs. Effects of inputs may well vary with number of children, e.g., if a mother works and puts children in daycare, reductions in contact time may be less if she has multiple children (as time with each was less to begin with) than if there is only one child.

[33] 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.
[34] A distributional assumption is needed for FIML or quasi-structural estimation, but can be avoided in IV or MOM.

A key issue in structural estimation is what mother's know, as this affects how they solve their dynamic optimization problem. For example, Bernal (2007) assumed mothers know the cognitive ability endowment of their child, but that it is unobserved by the econometrician. While assuming mothers know more than econometricians is reasonable, the assumption that they have complete information may be extreme. Hence one might consider alternative formulations where μ_s is split up into components the mother does and 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.[35]

Structural estimation also requires 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.[36] Thus, the strict exogeneity assumption of the fixed effects estimator is violated.

Structural estimation also involves assumptions on how 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 to fit

[35] For example, OLS and sibling fixed effects estimators implicitly assume that mothers do <u>not</u> 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.

[36] 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 thus 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).

the data. For instance, a typical specification would allow mothers to be heterogeneous in tastes for work (α_2), tastes for welfare participation (α_4), and tastes for child care utilization (α_5).

Solution of a mother's optimization problem requires calculating value functions at each point in the state space. Define Ω_t as the state at time t arising from decisions made up to t. Our model has five state variables that evolve endogenously: quarters of work experience since childbirth (E_t), work and childcare decisions during the immediately preceding period (h_{t-1}, I_{t-1}^c), cumulative quarters of childcare use ($\hat{C}_t$), and cumulative quarters of welfare participation (D_t). Thus, $\Omega_t = \{E_t, h_{t-1}, \hat{C}_t, D_t, I_{t-1}^c\}$.

Each woman also has a set of individual specific state variables that stay <u>fixed</u> 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. [Crucially, in Section 4.2, when we set up the quasi-structural approximation to the model, we must be careful to include <u>all</u> the state variables – both those in Ω_t and those that are individual specific].

A final issue is that the choice problem changes fundamentally when a child reaches roughly age 5, and he/she begins kindergarten. Then daycare 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.[37] Then, FIML estimation of the structural model requires that, at any 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 mothers' employment and childcare decisions on child cognitive ability is to form approximations to the decision rules for work and day care

[37] For instance, Bernal (2007) 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).

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 <u>all</u> 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.

Consider first the <u>work</u> 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:

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

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 $\varepsilon^*_{ft} = \mu_f + v_{ft}$.

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 $\varepsilon^*_{pt} = \mu_p + v_{pt}$.[38] Then, normalizing the value function for No-Work to 0, and assuming that v_{ft} and v_{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

[38] 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 restrictions. Nevertheless, the probability of full and part time work in the model are functions of all the state variables.

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 $\varepsilon_{ct}^* = \mu_c + v_{ct}$ that has a N(0,1) distribution.

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

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

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

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

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

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

where:

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

We define $\varepsilon_{st}^* = \mu_s + v_{st}$. Recall that A_o is the child's initial skill endowment, of which μ_s is the unobserved component. d_1 and d_2 are test dummies, for PPVT or PIAT-Math. Note that (13) includes interaction terms between 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.[39] This allows for heterogeneity in effects of childcare 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

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

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 daycare utilization, but do not enter the cognitive ability production function. Similarly, the state and time specific welfare and childcare subsidy rule parameters R_{st} and θ_{st} do not enter the wage equation (although, of course, the local demand condition variables do).

The structure of the model delivers additional exclusion and functional form restrictions, because the decision rules for work and childcare must depend on all the state variables, while some are excluded from the wage and cognitive ability production functions by the structural assumptions. For example, lagged full and part-time work, as well as work experience, enter the decision rules for work and daycare because they affect offer wages (equation (4)). But they do not enter the child cognitive ability production function directly. In 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 exclusion restriction is delivered by the 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 the quasi-structural model described here is the simpler single equation IV approach; estimate the cognitive ability production function alone, using instruments for cumulative income and childcare. As the sequential choice model is not made explicit, the instruments must capture average incentives to work and use daycare from birth up to time t. For instance, one might somehow average the welfare rule parameters over the period, or use many lagged values. In Bernal and Keane (2007) we try various different approaches to this problem.

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 needs 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 $\widehat{I}_t$ and $\widehat{C}_t$ with number of children to allow effects of income and daycare 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 these interactions below.[40] 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 daycare on child outcomes. Clearly, the assumption that marital status does not substantially alter the relationships of interest is quite strong, as it fundamentally alters the work decision.

5. The National Longitudinal Survey of Youth Data

5.1. Individual Level Data

We use data from the NLSY 1979 youth cohort (NLSY79). 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 over-samples of blacks, Hispanics, poor whites and the military. Interviews have been conducted annually from 1979 through 1994, and biannually since 1994. The NLSY79 has regularly collected pre- and postnatal care information from the sample 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/tests that are administered biennially for children of appropriate age.

Using the NLSY79 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 after 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 childcare, 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 childcare 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 childcare 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) 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

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[40] The number of children may itself be endogenous if there is a quality/quantity tradeoff. In an IV approach one can instrument for number of children and its interaction terms, as in Bernal and Keane (2007). Our model deals with this via correlation among the μ's. E.g., if women with many children tend to have low skill endowments, they will tend to have low μ's in the wage equation.

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 outcomes for the 1,219 children born too early for their mothers' behavior to be impacted by welfare reform. However, 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.[41]

Table 4 compares mean characteristics of single mothers in our sample with those of all single mothers, as well as all mothers, in the NLSY. Single mothers in our sample are very similar to those in the whole NLSY, despite our screen that the mother remain single for 5 years after childbirth. 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, more likely to be Hispanic or black (83% vs. 47%) and have a lower average wage before childbirth ($4.39 vs. $6.32 in 1983$).

Figure 1 displays employment and childcare 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 childcare, 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 childcare. 29% work full-time, 17% part-time and 26% stay home and use childcare.

5.2. Maternal Time Inputs, Income and Child Assessments

Unfortunately, the NLSY does not report the exact time a child spent in childcare. It only contains an indicator for whether the mother used childcare for at least 10 hours per week during the last month.[42] This information is not adequate to determine if a child was in full- or part-time childcare. However, by combining it with maternal work history information, we can make a reasonable determination about whether childcare was full or only part-time.

Thus, we use the childcare indicator, in conjunction with work history data, to construct:

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[41] A threat to validity of the welfare rule instruments is that rules may be correlated with women's skill levels. E.g., high skilled women might tend to live in States with stricter rules, or that moved towards welfare reform first. In Appendix 3 we present pre-reform average scores by State depending on whether the State implemented a Welfare Waiver prior to 1996, or implemented stricter rules after 1996. There is no significant difference in average test scores across the different types of States.

[42] 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).

(i) a dichotomous indicator of childcare use, the dependent variable in the childcare probit, and (ii) a measure of full-time, part-time or no childcare use, which we use to construct the cumulative childcare measure that appears in the cognitive ability production function (13).

Specifically, if a woman reported using at least 10 hours per week of childcare, she is assumed to have used childcare during the quarter.[43] If she worked full-time (375+ hours in the quarter) we assume childcare must have been full-time (which seems clear). On the other hand, if the mother did not work (<75 hours in the quarter) but reported using childcare, it seems highly likely the childcare 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 childcare was part-time in this case. We admit this assignment is not as obvious. However, if we assign full-time day care in this case it has almost no effect on our 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 childcare, $\widehat{C}_t$, and current childcare, I_t^c, as follows:

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

where t is the age of the child.

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

Another input in the child cognitive ability production function (13) is real household income. We measure it by summing income from all sources including wages, public assistance,

[43] We include formal care in a daycare center, nursery or preschool, and informal care by a relative or non-relative.

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 NLSY79 cognitive ability measures that we use as the dependent variable in (13) are 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.

Appendix 2 contains descriptive statistics for test scores. There is no clear age pattern in mean scores, as they are age adjusted. Means on the PPVT, PIAT-M and PIAT-R are roughly 80, 95 and 101. Standard deviations vary more by age than by test. For instance, at 5, the one age where we see all three tests, the standard deviations are 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 deviations 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 wage rate of $4.39 (1983 CPI$). Average work experience prior to childbirth was 4.7 years, and 72% of women had never been married. Average annual household income was $10.9 thousand (1983 CPI$). 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 childcare use, with the maternal wage and child cognitive ability production functions. Specifically, we maximize the likelihood given by approximate decision rules for work and daycare (see equation (11)), and the wage and test score density functions implied by equations (12) and (13).

Table 6 presents estimates of the cognitive ability production function (13) using several methods. Columns (1) and (2) present OLS and random effects (RE) estimates, respectively. Column (3) presents linear IV estimates, with the welfare and childcare subsidy rules and local demand condition variables in Table 1 used as instruments.[44] Finally, column (4) presents ML estimates from a special case of our "quasi-structural" model, where we assume effects of childcare and income on child outcomes are homogenous across types of children and mothers.

The OLS results imply use of childcare has no significant effect (either statistically or quantitatively) on children's achievement, and the RE estimates are similar. However, the IV estimates imply that OLS and RE estimates are severely upward biased. The linear IV estimate implies that one-quarter of full-time work and childcare use reduces a child's test scores by 0.81 percent. This translates into –3.2% for each year of childcare. The ML estimates of the quasi-structural model imply a similar result: an additional quarter of child care reduces a child's test scores by about 0.70 percent. This implies that one year of full-time maternal work and childcare use reduces test scores by roughly 2.8%. This is (.0279/.186)=0.15 standard deviations of the score distribution. Using results in Bernal and Keane (2007), this implies an effect on completed schooling of roughly .053 to .07 years (or about a 7.5% increase in college completion).

It is interesting that the linear IV and quasi-structural estimates are so similar. The IV estimates rely on welfare and daycare subsidy rules and local demand conditions as instruments. The quasi-structural approach relies on the same instruments to provide exclusion restrictions, and, in addition, uses 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 regarding the exact form of the decision rules for work and childcare (which the IV approach leaves implicit). Hence, each implements a selection correction (for the problem that children placed in daycare differ from those who are not) in a

[44] As we discussed in Section 4.2, linear IV requires instruments that capture effects of welfare rules and local demand conditions from the birth of the child up through time *t* on cumulative childcare use and income. To do this, in the first stage of our 2SLS procedure, we let $\widehat{C}_t$ and $\widehat{I}_t$ 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 instruments have the same coefficients at each age. In Bernal and Keane (2007), we consider alternative assumptions (e.g., allowing effects of instruments to differ by age), and show it has little effect on results.

somewhat different way. Thus, it is comforting the results are robust across the two approaches.

Cumulative household income is not statistically significant under any of the estimation methods except the quasi-structural approach. But in all cases the estimated effect of income since childbirth is quantitatively very small. In particular, a 1% increase in cumulative income induces a 0.019% increase in child test scores, which is (.000192/.1861) = 0.001 standard deviations. This effect 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 full-time rather than part-time after the birth of the child), then that extra income would induce a 1.9% increase in the child's scores (or .0192/.186 = .10 standard deviations). However, the negative effect of each additional half-year of childcare (required when the mother shifts from part- to full-time) is 1.4%, giving 7% over 5 years. Thus, while income has a positive effect on the child's achievement, it does not nearly offset 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 daycare 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 single-equation linear IV is that, by explicitly estimating the work and childcare decision rules, and including the mother's wage function as part of the system, we get a substantial efficiency gain. Indeed, the standard error on the childcare coefficient in the test score equation falls from .00333 to .00045, a factor of 7.4, giving us much greater confidence in the estimated effect size. As we will see 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 on 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 we can accommodate unobserved heterogeneity in effects of inputs on child cognitive outcomes. In Tables 7 through 12 we report estimates of the full model that includes interactions between initial child ability ($ln\ A_0$) and both cumulative child care and cumulative income (as in equation (13)).

The main results for the cognitive ability production function are presented in Table 7 column (2). The interaction between cumulative childcare and the child ability endowment is negative and statistically significant. This suggests that replacement of maternal time with daycare time has a more negative effect on outcomes for children with higher ability endowments. In other words, maternal time and the child ability endowment are complements in child cognitive ability production. However, the inclusion of both the linear term in cumulative childcare 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 childcare and income, as a function of $ln\ A_0$. This shows how effects of inputs differ with $ln\ A_0$.

At the mean value of the child ability endowment, the estimated effect of an additional quarter of full-time maternal work and childcare 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).

Figure 2 also shows that the effect of childcare ranges from -.52% per quarter (-2.1% per year) for a child with an ability endowment two standard deviations below average to -.83% per quarter (-3.3% per year) for a child with an endowment two standard deviations above average. In contrast, the interaction of income with lnA_0 is statistically and quantitatively insignificant.

The third column of Table 7 reports a special case of the model that allows only <u>observed</u> heterogeneity in daycare effects. We interact mother's education, one of the determinants of the child ability endowment A_0, with cumulative child care. The interaction is highly significant (t=-6) and negative, implying that replacement of mother's time with alternative day care provider time has a more negative effect on child cognitive outcomes for more educated mothers.

We de-mean education prior to interacting it with cumulative childcare. Hence, in column (3), the linear childcare term is interpretable as the effect of childcare on child outcomes for a mother with average education (11.2 years). The 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 childcare is -2.8-(2)(-.48) = -1.8% per year. Thus, the adverse effect of childcare use is much smaller for less educated mothers.

Bernal and Keane (2007) obtain very similar point estimates using linear IV, i.e., a linear daycare effect of -.0062 and an interaction with mother's education of -.00174. But the interaction has a standard error of .0010, and hence is only significant at the 10% level.[45] 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. Table 9 presents estimates of the initial and re-employment wage equation. All parameters have expected signs and reasonable magnitudes. For example, an additional year of education is associated with 4% increase in initial wages. Similarly, the age and age^2 coefficients imply that, at age 20, an additional year of potential experience (i.e., age) is associated with a 4.5% increase in the initial wage.[46] The local demand conditions are highly significant with expected signs.

Tables 10 and 11 present estimates of the work and childcare 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 of childcare use (although the latter effect is only marginally significant). The indicator for whether a woman might be subject to a time limit or work requirement, I[TL_HIT or WR_HIT] has large and highly significant positive coefficients in the value functions for both full- and part-time work and childcare utilization.[47] A

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[45] Nevertheless, Bernal and Keane (2007) find that if a mother's education is 4 years above the sample average, the negative day care effect increases from –.62% to –1.31%. The later estimate has a standard error of .41, obtained via the delta method, and hence a t-stat of –3.19.

[46] 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.

[47] Due to collinearity between 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 problem forced us to combine indicators for whether a woman could have been hit by a binding time limit or work requirement, TL_HIT and WR_HIT, into a single indicator for whether she could have been hit by either a time limit or work requirement.

longer benefit receipt time limit significantly reduces the probability a mother works, although the effect on daycare 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 a mother works full-time, and lowers the probability of using daycare. As expected, both the flat and percentage earnings disregards increase the probability of work.

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

Turning to the local demand conditions, the 20^{th} percentile wage in a woman's State of residence significantly increases the probability of full-time work and reduces that of part-time work. The service sector employment share significantly increases the probability of work.

Some of the estimates are less intuitive. Higher welfare grant levels are associated with a higher probability of work and a lower probability of daycare. 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 types of children placed in daycare. The correlation between 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.[48] On the other hand, the permanent unobservables in the full and part-time work equations are positively correlated with the child's unobserved ability endowment. Thus, as expected, working mothers tend to have relatively high skilled children, biasing OLS estimates of work/daycare effects in a positive direction. The

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

permanent error component in the childcare 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 frequencies in Figure 1, based on 15,000 simulated individuals. The model fits the choice data quite well, particularly for the most common alternatives, i.e., stay at home/do not use childcare and work/use childcare. 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 – at those ages, the model slightly understates the percent using childcare but not working. The model also provides a good fit to wages by mother characteristics and test scores by child age (see Figure 4 and Table 14).

6.4 Robustness Checks

An important question is whether our results are robust to alternative specifications of the cognitive ability production function, choice of sample, etc. Table 15 addresses this issue by presenting estimates of some alternative versions of the model. The first column reproduces our main results from Table 7 column (2). The second column reports results when we separately control for number of siblings aged 0-5 and 6-17 (both in the production function and the daycare/work decision rules). As expected, the negative effect of siblings on child test outcomes is much greater when siblings are of a similar age (0-5), because this has a more direct impact on maternal time and money resources available to the child. However, this change in specification has almost no effect on the estimated effect of childcare. At the mean of $ln\ A_0$, the effect of a quarter of full-time work/daycare is -0.67% under the baseline model and -0.70% in column (2).

Another important issue is sensitivity of our results to controls for age of the mother. The concern is that welfare policy variables, which provide key exclusion restrictions to help identify our selection model, are correlated with mothers' age at childbirth; due to the timing of welfare reform, younger mothers in the NLSY are less likely to face a strict welfare policy regime.[49] Hence, welfare policy rules are endogenous in the child outcome equation if (i) mother's age at birth *does* affect child outcomes or is correlated with the child skill endowment, and (ii) we fail to include adequate controls for mother's age at birth in the cognitive ability production function.

[49] For children born prior to 1990, it is unlikely that waivers could have influenced their mothers' labor supply behavior prior to the child reaching age 6. Post-1990, all births in the data are to mothers in their 20s and 30s, while, pre-1990, a significant fraction were to teenage mothers.

We address this issue in columns (3)-(4). In (3) we remove the age controls entirely.[50] This has almost no impact on the estimated daycare effect. At the mean of $ln\ A_0$, the estimated effect is –0.66% per quarter. In column (4), we restrict the sample to mothers who were at least 24 years old at the time of childbirth. This also has little impact on the estimated daycare effect, which is –0.61% at the mean of the data. There is no doubt that the welfare rules are highly correlated with mother's age at birth, so we take the insensitivity of results to controls for age as evidence that mother's age is not, *ceteris paribus*, quantitatively important for child outcomes.

A key issue is whether timing of childcare matters. In column (5), we decompose childcare use into that during the first year vs. that during the 2nd through 5th years. Here the estimates imply a substantial difference. At the mean of $ln\ A_0$, the estimated effect is +0.63% per quarter in the first year, and –0.90% per quarter in the 2nd through 5th years. Thus, it appears the maternal time input is more important for older children (i.e., those who are learning to read). [51]

Finally, one threat to the validity of our over-identifying instruments is that they depend on both policy variation and fertility decisions, as some of them are constructed based on actual household size and children's ages. Thus, we present an additional exercise in which the exclusion restrictions do not depend on either of these. The AFDC/TANF benefit BEN_{ist} (which depends on number of children) is replaced by the maximum *potential* real monthly benefit for families with one and two children ($BEN(1)_{st}$ and $BEN(2)_{st}$), assuming zero earnings, in the mother's State of residence. Similarly, we replace $EITC_{ist}$ by the EITC subsidy rates for families with one and 2+ children ($EITC(1)_{st}$ and $EITC(2)_{st}$ respectively). In addition, we exclude instruments that depend upon ages of children such as *TL_HIT, REMAIN_TL_ELIG, ELAPSED_TL_HIT, REMAIN_ELIG, WR_HIT,* and *ELAPSED_WR_HIT*. These results are presented in column (6). At the mean of $ln\ A_0$, the estimated effect is –0.74% per quarter, compared with –0.67% in the baseline specification (column (1)). Thus, eliminating instruments that depend on fertility decisions has little impact on the estimated daycare effect.

As we noted in Section 4, there are advantages and disadvantages to each of the quasi-structural, fully structural and single equation IV approaches. An advantage of IV is one can

[50] Recall that the baseline specification controls for mother's age at birth, age squared, and indicators for age less than 20 or greater than 32.

[51] This result contradicts the National Research Council and Institutes of Medicine (2000), who conclude there is compelling evidence that maternal employment in the first year can have a negative effect on infant development. Our reading of the prior evidence is rather different. First, most of the studies they cite fail to control for the fact that women who work in the first year after childbirth are systematically different from women who don't. Second, as we detail in Bernal and Keane (2007), the results of the prior literature are not really so consistent.

estimate models quickly, so robustness to many alternative specifications can be checked. This is difficult in quasi-structural/fully structural approaches, as estimation is so time consuming.

Our companion paper Bernal and Keane (2007) adopts a linear IV approach, and examines a much more extensive range of specifications for the cognitive ability production than we examine here. There, we find that an estimated "average" childcare effect of roughly –0.73% per quarter is remarkably robust to changes in the specification in the production function, as well as to the instruments used in estimation. We also find, consistent with results here, that the negative effect of day care is more pronounced when the child has a higher ability endowment and/or the mother is more educated. We also look at daycare quality, and find that high quality daycare (i.e., formal center-based care) does not have any detrimental effects on children.[52]

7. Conclusions

This paper evaluates the effects of maternal work and childcare use on child cognitive development, using the sample of single mothers in the National Longitudinal Survey of Youth (NLSY). In particular, we assess the effects of maternal vs. alternative care provider time inputs, and household income, on child cognitive test scores recorded at ages 3, 4, 5 and 6. To deal with potential bias created by unobserved heterogeneity of mothers and children, and systematic selection of certain types of children into childcare, we develop a model of mothers' employment and child-care decisions. Closely guided by this model, we obtain approximate decisions rules for employment and childcare use, and estimate these jointly with the child's cognitive ability production function – what we term 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/childcare use created by variation 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 variables provide natural exclusion restrictions, as it is plausible they enter decision rules for employment and daycare use, while not entering the child cognitive ability production function. These instruments are also quite powerful, in that they explain a substantial part of the variation in work and childcare use by single mothers.

[52] Indeed, our point estimates generally imply that formal day care has a positive effect for children of poorly educated mothers. However, unlike our other results, the significance of this result is not robust to different specifications of the instrument list.

Our results imply that a mother working full-time, while placing a child in daycare, for one full year, reduces the child's cognitive ability test score by 2.7% on average, or 0.14 standard deviations of the score distribution. We estimate a very similar 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 daycare may differ those who are not) in a somewhat different way. Thus, it is comforting results are robust across the two approaches. However, the quasi-structural approach leads to a substantial efficiency gain, reducing the standard error on the daycare effect by a factor of roughly 7.4 and giving us much greater confidence in the estimate.[53]

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 childcare 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 childcare is –2.8%, while for a mother with only 9.2 years of education, the negative effect of a year of childcare use is –2.8 + (2)(-.48) = -1.8%.

We also find that the effect of household income since childbirth is quantitatively small. In particular, a 100% increase in cumulative household income is associated with an increase of roughly 1.9% in test scores. However, the negative effect of <u>each</u> additional half-year of childcare (required for the mother to double work hours) is 1.4%, giving 7% over 5 years. Thus, while income has a positive effect on a child's achievement, it does not nearly offset the effect of maternal separation. One should be careful not to conclude from this that income is unimportant. Since we control 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.[54]

Our study of the case of single mothers extends earlier work by Bernal (2007), who

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[53] In a simplified version of our quasi-structural model that assumes homogeneous effects of child care, 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). Using linear IV, the coefficient is -.00807 with a standard error of .00333 (t = -2.42).

[54] 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).

estimated 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 1.8% reduction in child cognitive ability test scores. A key motivation of our work is to see if that result generalizes from married to single mothers. Our estimate for single mothers is larger (2.7%), but the similarity of the results is fairly striking. Bernal (2007) also found heterogeneity in childcare effects (with child ability endowments) similar to what we find here.

Obviously, aside from the technical advantage that arises because of the presence of highly plausible instruments (i.e., work behavior of single mothers is strongly influenced by welfare rules and local demand conditions), the study of single mothers is of special policy interest as well, given that recent welfare policy changes have substantially increased their work and daycare 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.

In interpreting our results, it is important to remember that we do not incorporate choice of type/quality of childcare in our model. So we are basically estimating the effect of the average type of childcare that single mothers use. Including choice of quality in a structural or quasi-structural framework is difficult, because it greatly expands the choice set, but it is fairly easy in a linear IV setting – provided the instruments help predict quality choice. In our companion paper Bernal and Keane (2007), which adopts a linear IV approach, we find that type of daycare is very important. Most single mothers use informal methods that are of relatively low quality and have significant negative effects on children. But high quality center-based care does not have adverse effects.

Finally, an important caveat, noted in Section 4, is that our model assumes day care use reduces the maternal time input one-for-one. This is unavoidable, as we lack data on maternal "quality" contact time with the child. Thus, our estimated day care effect may not capture the pure effect of substituting child care for maternal time; it may also capture adjustments to quality time and goods inputs that mothers make simultaneously with placing children in childcare.

References

Baydar, N. and J. Brooks-Gunn, 1991, "Effects of Maternal Employment and Child Care Arrangements on Preschoolers' cognitive and Behavioral Outcomes: Evidence from Children of the National Longitudinal Survey of Youth", *Developmental Psychology* 27(6), 932-945.

Bernal, R., 2007, “The Effect of Maternal Employment and Child Care on Children’s Cognitive Development”, forthcoming *International Economic Review,* 2008.

Bernal, R. and M.P. Keane, 2007, “Child Care Choices and Children’s Cognitive Achievement: The Case of Single Mothers”, manuscript, Universidad de los Andes, UTS and Arizona State University.

Blau, D., 1999, "The Effects of Child Care Characteristics on Child Development", *The Journal of Human Resources*, XXXIV, 4.

Blau, D., 1999b, “The Effect of Income on Child Development”, *Review of Economics and Statistics,* 81(2): 261-276, May.

Blau, F. and A. Grossberg, 1992, "Maternal Labor Supply and Children's Cognitive Development", *The Review of Economics and Statistics* 74(3), 474-481.

Burchinal, M.R., S. Ramey, M. Reid and J. Jaccard, 1995, “Early Child Care Experiences and their Association with Family and Child Characteristics during Middle Childhood”, *Early Childhood Research Quarterly,* 10: 33-61.

Cameron, S.V. and J.J. Heckman, 1998, "Life Cycle Schooling and Dynamic Selection Bias: Models and Evidence for Five Cohorts of American Males", *Journal of Political Economy*, Vol, 106, No.2.

Caughy, M., J. DiPietro and D. Strobino, 1994, “Daycare Participation as a Protective Factor in the Cognitive Development of Low-Income Children”, *Child Development* 65:457-471.

Chase-Lansdale, P.L., R. Moffitt, B. Lohman, A. Cherlin, R. Coley, L. Pittman, J. Roff, E. Votruba, 2003, “Mothers’ Transitions from Welfare to Work and the Well-Being of Preschoolers and Adolescents”, *Science,* 299(March):1548-1552.

Cunha, F., J. Heckman, L. Lochner, and D. Masterov. (2006): “Interpreting the Evidence on Life Cycle Skill Formation,” in E. Hanushek and F. Welch (eds.), *Handbook of the Economics of Education*, 697-812. Amsterdam: North-Holland.

Duncan, G. and NICHD Early Child Care Research Network, 2003, “Modeling the Impacts of Child Care Quality on Children’s Preschool Cognitive Development”, manuscript Northwestern University.

Fang, H. and M. Keane, 2004, “Assessing the Impact of Welfare Reform on Single Mothers”, *Brookings Papers on Economic Activity* Vol. 1.

Geronimus, A., Korenman, S., and M. Hillemeier, 1994, "Does Young Maternal Age Adversely Affect Child Development? Evidence from Cousing Comparisons in the United States", Population and Development Review 20, 585-609.

Han, W., Waldfogel, J., and J. Brooks-Gunn, 2001, “The Effects of Early Maternal Employment on Later Cognitive and Behavioral Outcomes”. *Journal of Marriage and the Family*, 63(2): 336-354.

Haveman, R. and B. Wolfe, 1994, Succeding Generations: On the Effects of Investments in Children. New York: Russell Sage Foundation.

James-Burdumy, S., 2005, "The Effect of Maternal Labor Force Participation on Child Development", *Journal of Labor Economics* Vol. 23(1): 177-211.

Keane, M., 1992, A Note on Identification in the Multinomial Probit Model, *Journal of Business and Economic Statistics*, 10:2, p. 193-200.

______. 1994. A Computationally Practical Simulation Estimator for Panel Data, *Econometrica*, 62:1, p. 95-116.

Keane, M. and R. Moffitt, 1998, “A Structural Model of Multiple Welfare Program Participation and Labor Supply”, *International Economic Review*, Vol. 39, No. 3, pp. 553-589

Keane, M. and K. Wolpin, 1997, "The Career Decisions of Young Men", Journal of Political Economy, 105:3, p. 473-522.

______. 2001. “The Effect of Parental Transfers and Borrowing Constraints on Education Attainment”, *International Economic Review* 42(4), pp. 1051-1103.

______. 2002a, “Estimating Welfare Effects Consistent with Forward-Looking Behavior. Part I: Lessons from a Simulation Exercise”, *Journal of Human Resources* 37(3):570-599.

______. 2002b, “Estimating Welfare Effects Consistent with Forward-Looking Behavior. Part I: Empirical Results”, *Journal of Human Resources* 37(3):600-622.

______. 2006, “The Role of Labor and Marriage Markets, Preference Heterogeneity and the Welfare System in the Life Cycle Decisions of Black, Hispanic and White Women”, Working Paper, University of Pennsylvania.

Lamb, M., 1996, “Effects of Nonparental Child Care on Child Development: An Update”, *The Canadian Journal of Psychiatry*, 41:330-342.

Lopez, R., 2003, "Are Children of Young Mothers Disadvantaged Because of Their Mother's Age or Family Background?", Child Development 74, 465-474.

Love, J.M., P. Schochet and A. Meckstroth, 1996, "Are They in Real Danger? What Research Does -And Does not- Tell Us About Child Care Quality and Children's Well-being", Plainsboro NJ: Mathematica Policy Research (ERIC Document Reproduction Service No. ED145 030).

Moffitt, R., 1983, “An Economic Model of Welfare Stigma”, *The American Economic Review*, Vol. 73, No. 5, pp. 1023-1035.

______. 1992, “Incentive Effects of the U.S. Welfare System: A Review”, *Journal of Economic Literature,* 30(1), pp. 1-61.

National Research Council and Institutes of Medicine, 2000, *From Neurons to Neighborhoods: The Science of Early Childhood Development*, Shonkoff, J. and D. Phillips, eds. Washington D.C. National Academy Press.

Parcel, T. and E. Menaghan, 1990, "Maternal Working Conditions and Children's Verbal Facility: Studying the Intergenerational Transmission of Inequality from Mothers to Young Children", *Social Psychology Quarterly* 53: 132-147.

Parcel, T. and E. Menaghan, 1994, "Early Parental Work, Family Social Capital, and Early Childhood Outcomes", *American Journal of Sociology* 99(4), 972-1009.

Rosenzweig, M. and P. Schultz, 1983, "Estimating a Household Production Function: Heterogeneity, the Demand for Health Inputs, and Their Effects on Birth Weight", *The Journal of Political Economy*, Vol. 91, Issue 5.

Rosenzweig, M. and K. Wolpin, 1994, "Are There Increasing Returns to the Intergenerational Production of Human Capital? Maternal Schooling and Child Intellectual Achievement", *The Journal of Human Resources*, Vol. 29, Issue 2.

Rosenzweig, M.R., and Wolpin, K. I., 2000, "Natural 'Natural Experiments' in Economics", *Journal of Economic Literature*, Vol. XXXVIII, no. 4, 827--874.

Ruhm, C., 2002, "Parental Employment and Child Cognitive Development", NBER Working Paper No. 7666.

Studer, M., 1992, "Quality of Center Care and Preschool Cognitive Outcomes: Differences by Family Income", *Sociological Studies of Child Development*, Vol. 5, P. Adler and P. Adler, eds.

Todd, P. and K. Wolpin, 2003, "On the Specification and Estimation of the Production Function for Cognitive Achievement", *Economic Journal* Vol. 113(485): 3-33.

______. 2005, "The Production of Cognitive Achievement in Children: Home, School and Racial Test Score Gaps", manuscript, University of Pennsylvania, February.

U.S. House of Representatives, Committee on Ways and Means. 2000. *The 2000 Green Book: Background Material and Data on Programs within the Jurisdiction of the Committee on Ways and Means*.

Vandell, D. and J. Ramanan, 1992, "Effects of Early and Recent Maternal Employment on Children from Low-income Families", Child Development 63(4), 938-949.

Waldfogel, J., W. Han and J. Brooks-Gunn, 2002, "The Effects of Early Maternal Employment on Child Cognitive Development," *Demography*, May 39(2): 369-392.

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	
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
I_t	Cumulative income					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

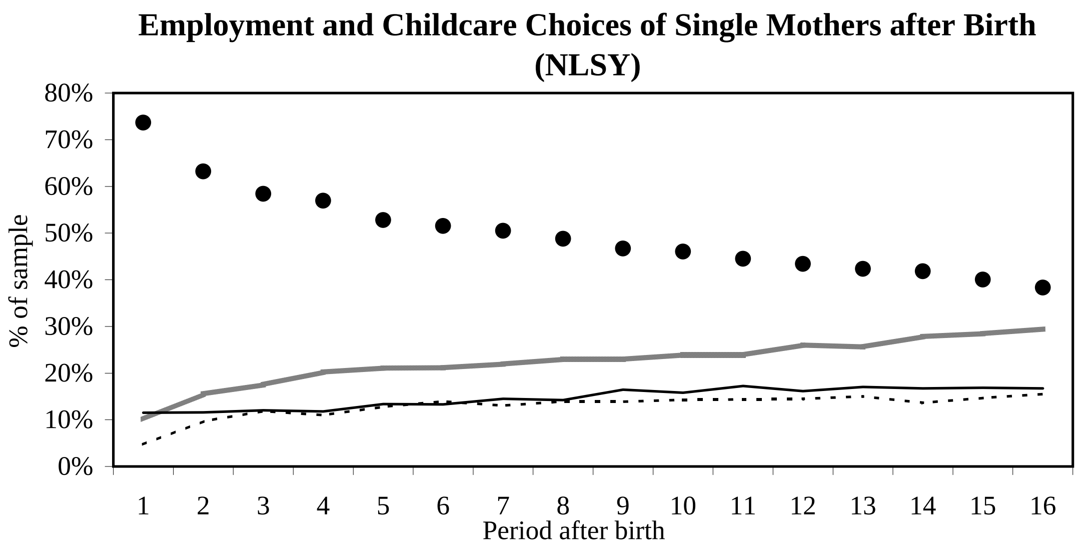
Table 15

Test Score Equation
Robustness Checks: Children's ages, mother's age and age-specific effects

Dep. Variable: log(test score)	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative Child Care	0.02529	0.02860	0.02778	0.03046		0.03451
	(0.0134) **	(0.0103) **	(0.0109) **	(0.0126) **		(0.0125) **
Cumulative Child Care 1st year					0.10170	
					(0.0479) **	
Cumulative Child Care after 1st year					0.04080	
					(0.0129) **	
Log(Cumulative Income)	0.01159	0.00111	0.00352	0.02144	0.01148	0.01471
	(0.0862)	(0.0626)	(0.0675)	(0.0932)	(0.0607)	(0.0867)
Total Childcare * $\ln A_o$	-0.00686	-0.00758	-0.00729	-0.00781		-0.00899
	(0.0029) **	(0.0022) **	(0.0023) **	(0.0027) **		(0.0027) **
Childcare 1st year * $\ln A_o$					-0.02034	
					(0.0101) **	
Childcare after 1st year * $\ln A_o$					-0.01062	
					(0.0027) **	
Log (Income) * $\ln A_o$	0.001703	0.00609	0.00469	0.00623	0.005937	0.000998
	(0.01845)	(0.0133)	(0.0143)	(0.0200)	(0.01290)	(0.01854)
Mother's education	0.01297	0.01285	0.01287	0.0128018	0.01295	0.01339
	(0.0014) **	(0.0011) **	(0.0011) **	(0.0014) **	(0.0011) **	(0.0015) **
Mother's AFQT	0.00132	0.00126	0.00129	0.00126	0.00130	0.00131
	(0.0002) **	(0.0001) **	(0.0001) **	(0.0002) **	(0.0001) **	(0.0002) **
Mother's AFQT missing	0.01956	0.01549	0.01770	0.01101	0.01807	0.02075
	(0.01489)	(0.01044)	(0.01311)	(0.0272)	(0.0104)	(0.0173)
Mother's age	-0.00355	-0.00049		-0.00204	-0.00125	
	(0.0058)	(0.0083)		(0.0128)	(0.0441)	
Mother's age squared	0.00001	-0.00003		-0.00002	-0.00003	
	(0.0001)	(0.0238)		(0.0002)	(0.0072)	
I[mother's age<20]	0.06862	0.06950			0.06853	0.07240
	(0.00858) **	(0.00648) **			(0.0064) **	(0.0088) **
I[mother's age>=33]	0.03462	0.03562		0.03535	0.03461	0.03616
	(0.01335) **	(0.01013) **		(0.0125) **	(0.01056) **	(0.01342) **
I[worked before]	0.02841	0.02807	0.02823	0.02795	0.02074	0.02902
	(0.00413) **	(0.00326) **	(0.00369) **	(0.0056) **	(0.00318) **	(0.00442) **
EXPBEF	0.00314	0.00321	0.00317	0.00328	0.00318	0.00318
	(0.00047) **	(0.00037) **	(0.00033) **	(0.0004) **	(0.00038) **	(0.00046) **
Gender	-0.01687	-0.01662	-0.01651	-0.01659	-0.01672	-0.01664
	(0.0032) **	(0.0025) **	(0.0028) **	(0.0036) **	(0.0024) **	(0.0033) **
Race	-0.04611	-0.04590	-0.04613	-0.04622	-0.04589	-0.04724
	(0.0056) **	(0.0043) **	(0.0047) **	(0.0065) **	(0.0042) **	(0.0057) **
Birthweight	0.05759	0.05621	0.05673	0.05614	0.05724	0.05820
	(0.0042) **	(0.0031) **	(0.0034) **	(0.0046) **	(0.0032) **	(0.0042) **
Number of siblings	-0.01590		-0.01597	-0.01549	-0.01552	-0.01613
	(0.0013) **		(0.0011)	(0.0013) **	(0.0010) **	(0.0013) **
Number of siblings 0-5 yrs of age		-0.02033				
		(0.0015) **				
Number of siblings 6-17 yrs of age		-0.00667				
		(0.0012) **				
Child's age	0.03980	0.03937	0.03644	0.03973	0.03958	0.04000
	(0.0047) **	(0.0042) **	(0.0044) **	(0.0062) **	(0.0043) **	(0.0047) **
Constant	4.39550	4.37606	4.37106	4.40033	4.38648	4.36419
	(0.0792) **	(0.0626) **	(0.0235) **	(0.1804) **	(0.0619) **	(0.0831) **
MSE_{ML}	0.0297	0.0294	0.0294	0.0296	0.0295	0.0296
Fraction due to permanent	0.2268	0.2237	0.2231	0.2286	0.2256	0.2321
Number of observations	3,787	3,787	3,787	1,680	3,787	3,787

Test dummies not reported. Estimates are almost identical to those in Table 6.
(1) Baseline model (equation (2) in Table 7)
(2) Baseline equation splitting up number of siblings by age range.
(3) Baseline equation without mother's age controls.
(4) Subsample of mothers 24 years of age and older.
(5) Baseline model but child care is split up into child care in first year and child care after first year.
(6) Excludes instruments that depend upon mother's actual household size (replacing them by state-specific rules) and children's ages.
** Significant at 5%; * Significant at 10%

Figure 1

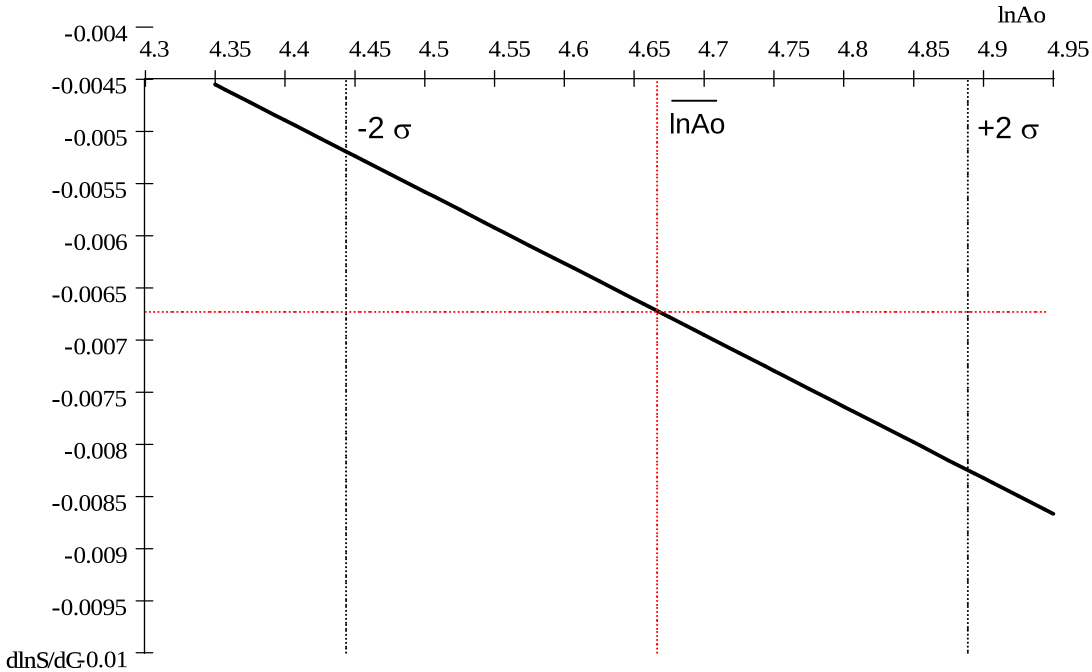


Note: The first 12 periods correspond to quarters (3-months) and the last four correspond to semesters.

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

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

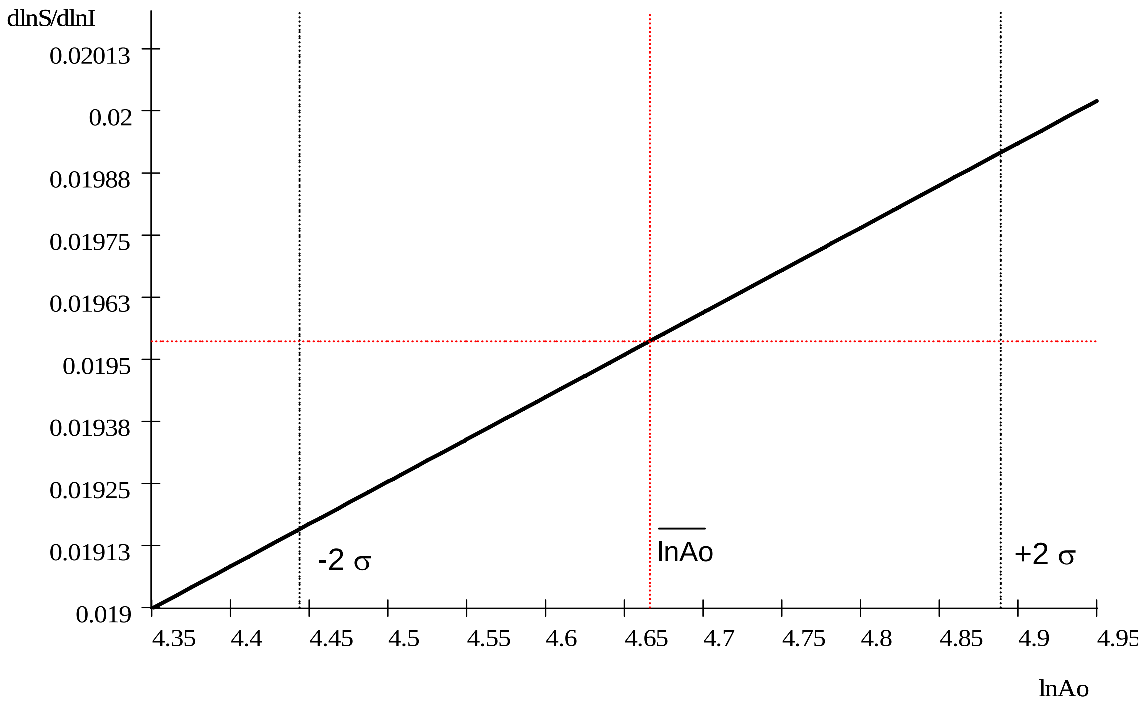


Figure 3

Model Fit to Choice Distributions

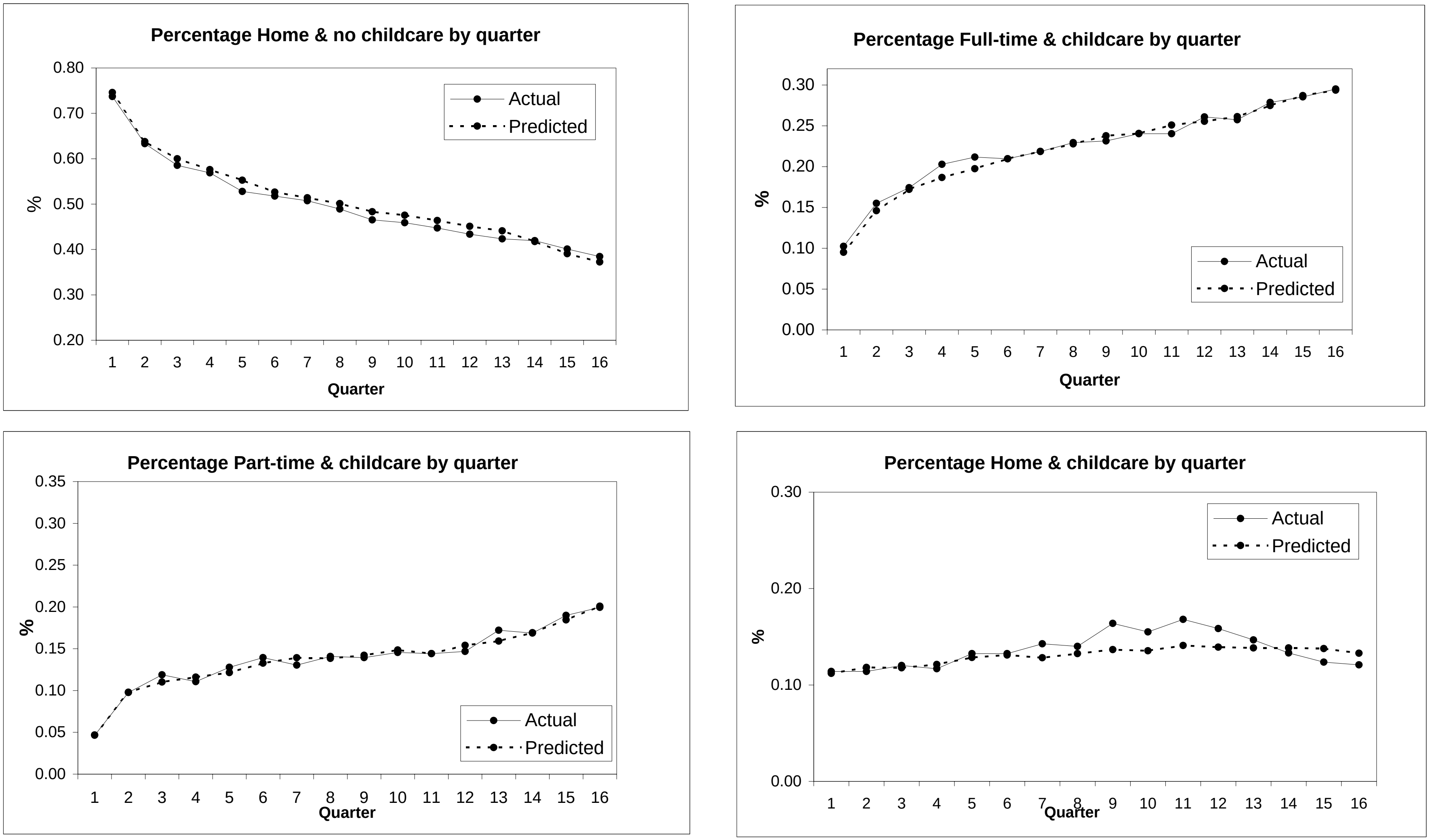
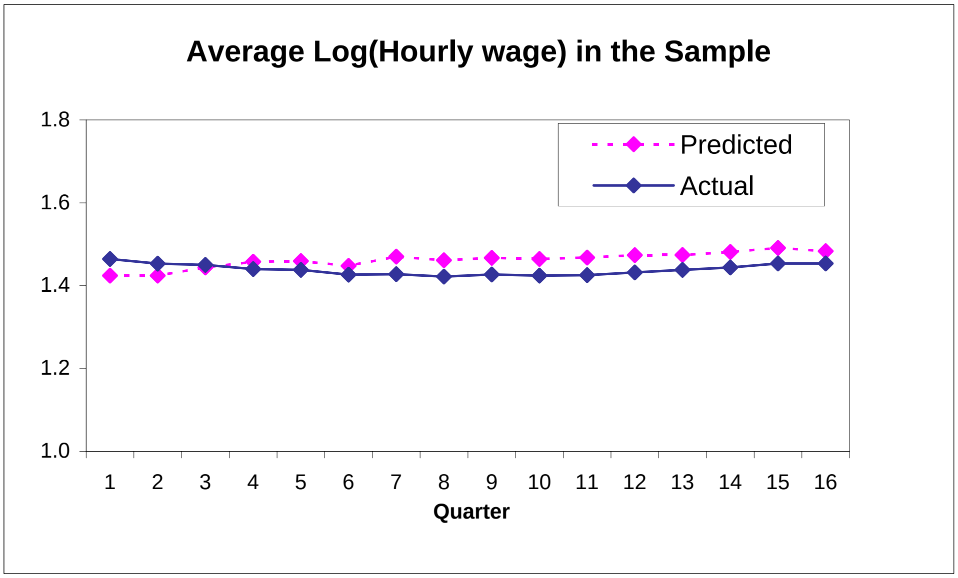
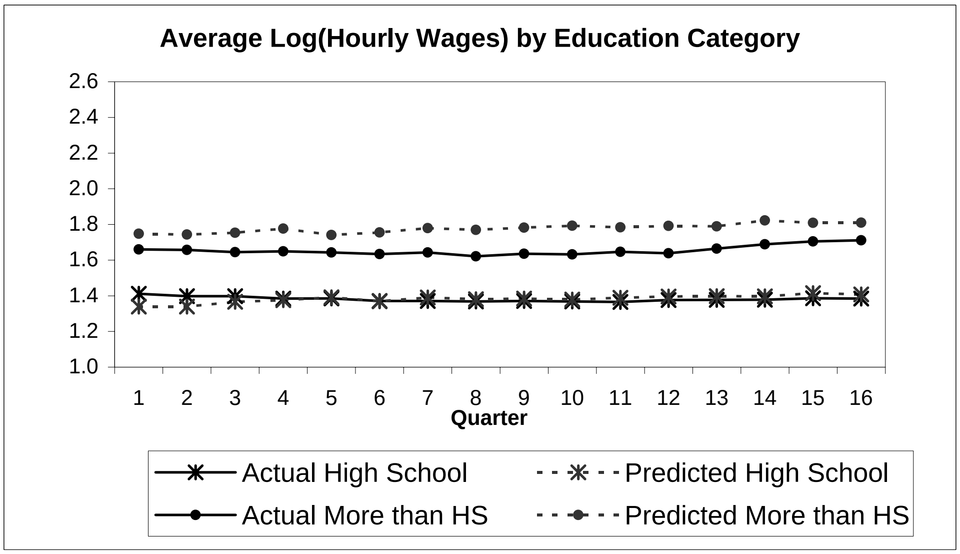


Figure 4



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



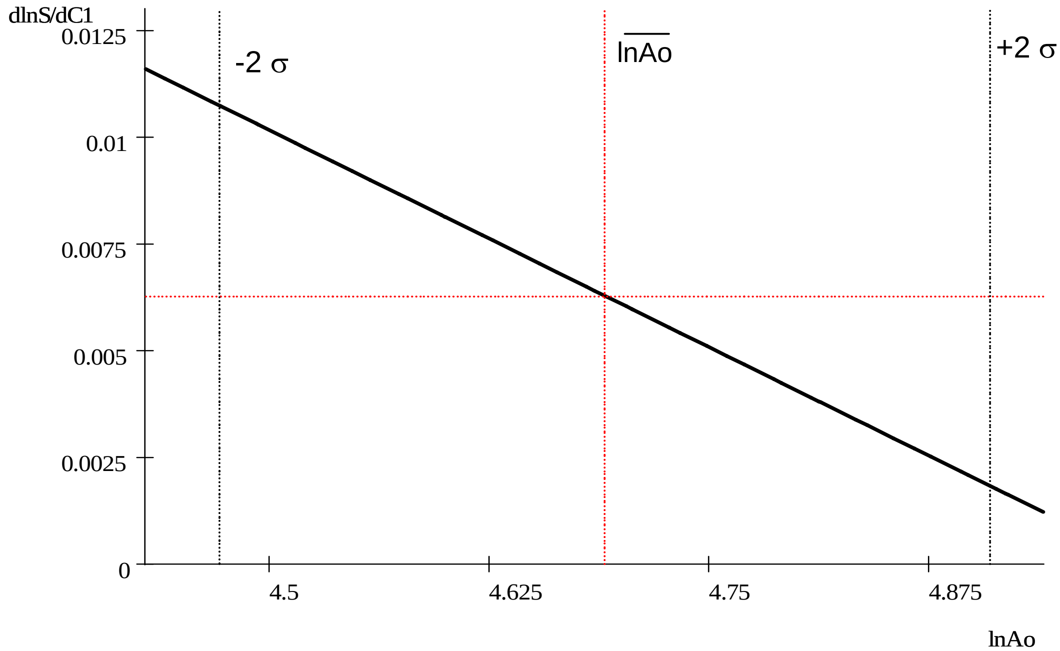
Average Log(Hourly Wages) by Education Category
2.6
2.4
2.2
2.0
1.8
1.6
1.4
1.2
1.0
1 2 3 4 5 6 7 8 9 10 11 12 13 14 15 16
Quarter
Actual High School
Predicted High School
Actual More than HS
Predicted More than HS

Figure 5

Age-specific Effect of Child Care Use on Cognitive Ability

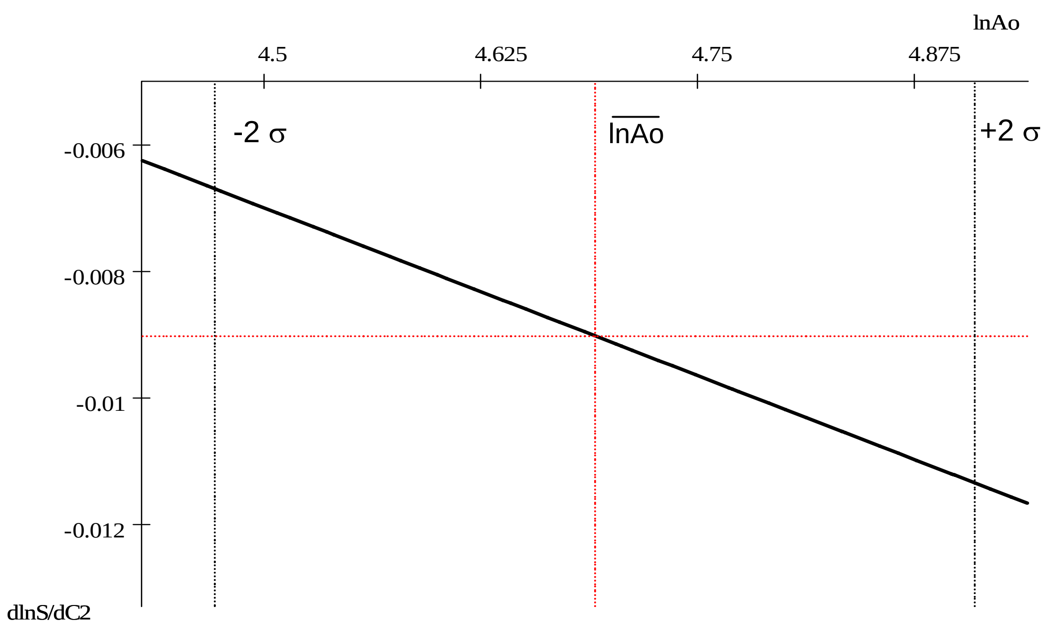
Effect of Child Care Used during the First Year

$$dlnS_t/dC_{1t}=0.1017-0.02034lnA_o$$



Effect of Child Care Used after the First Year

$$dlnS_t/dlnC_{2t}=0.04080-0.01062lnA_o$$



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