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

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Abstract

This paper evaluates the effects of maternal time inputs and alternative providers' time inputs on children's cognitive development using the sample of single mothers in the National Longitudinal Survey of Youth. In order to deal with the selection problem that arises because of 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." We take advantage of the plausibly exogenous variation in employment and child-care choices generated by the differences in welfare regulations across states and over time introduced by the welfare reform legislation of 1996, and prior to that by Section 1115 Welfare Waivers, to help identify the selection model. These welfare rules provide natural exclusion restrictions, as it is plausible that they enter the decision rules for employment and day care use, while not entering the child cognitive ability production function directly. The instruments are quite powerful, in the sense that they explain a substantial part of the variation in work and day care use by single mothers.

Our results imply that if a mother works full-time, while placing a child in day care, for one full year, this reduces the child's cognitive ability test score by 3.0%, which is 0.135 standard deviations. The result we obtain here is very similar to what we obtained in Bernal and Keane (2005), where we adopted a single equation instrumental variable (IV) approach. There, our estimates implied that one year of full-time work and day care use would lower a child's test scores by 2.9%. Each approach relies on somewhat different identifying assumptions. Thus, it is comforting that results are so robust across the two approaches.

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1. Introduction

The effect of maternal time inputs on children's development has been widely analyzed, especially in the psychology and sociology literature. Economists have also realized the importance of this question. Recent studies in the human capital literature, such as Keane and Wolpin (1997) and Cameron and Heckman (1998), suggest that educational attainment and labor market outcomes in later life (i.e., wages and employment) are largely determined by skill "endowments" that are already in place by around age 16. But the early determinants of age 16 skill "endowments" remain largely a black box. This suggests that the human capital literature should place more emphasis on investments in human capital that occur at earlier ages. Such investments include parental time and goods inputs into child development.

While causality is difficult to ascertain, extensive research has shown that children's early cognitive achievements are strong *predictors* of a variety of outcomes later in life: the high achievers are more likely to have higher educational attainment and higher earnings; and less likely to have out-of-wedlock births, be on welfare or participate in crime. For this reason, understanding the determinants of cognitive ability at early ages would appear to be critical for the design of public policy aimed at improving labor market outcomes. However, the question of what determines children's cognitive achievement in general, and the role of parental time and goods inputs in particular, remains largely unresolved.

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

There are two key potential sources of selection bias that arise in this context: (1) Women that work/use child care may be systematically different from women that do not work/do not use child care; (2) The child's cognitive ability itself may influence the mother's decisions of whether to work or not and/or place the child in daycare. In the case of (1), for example, a woman with higher skills is more likely to have a child with high cognitive ability and also more likely to work. Then, a statistical analysis would attribute the effect of this woman's higher skills to employment, and the estimated effects of maternal employment on child's cognitive outcomes would be upwardly biased. In the case of (2), mothers of low ability endowment children may choose to compensate them by spending more time with them, in which case mothers are more likely to work if they have high ability children. Again, the estimated effect of maternal employment on child's cognitive outcomes would be upwardly biased. Clearly, these sample selection issues make evaluation of the effects of women's decisions on child outcomes very difficult.

We believe that the data on single mothers in the NLSY79 provides an important opportunity to address these selection problems. A subset of women in this sample was affected by the substantial reform of the U.S. welfare system that occurred in the mid-90s. During this period, there were important changes in welfare rules, generated by welfare waivers and the Temporary Aid to Needy Families (TANF) program, along with increased day care subsidy spending, through 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 large increases for certain subgroups[2].

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 and use day care in the period 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 can help to identify the effect of maternal work and day care use on child outcomes.[3]

While this discussion gives an intuition for our approach, it may seem to suggest a simple before and after welfare reform comparison of test score outcomes and levels of maternal work – as in the natural experiment IV literature - which is, in fact, a gross oversimplification of the approach we actually implement. As Rosenzweig and Wolpin (2000) have stressed in a range of

[2] This increase has been even more dramatic for single mothers that have never been married (from 57% to 78%), with low educational attainment (from 40% to 61%), with children aged 0-5 (from 59% to 78%), with more than 3 children (from 34% to 67%), or who are African-American (from 57% to 76%).

[3] This description may make it sound as if there was point in time when welfare rules became stricter in the sense of being more conducive of work. But this is just an oversimplification to facilitate exposition. A key aspect of the federal reform, both in waivers and PRWORA 1996, was to give States greater flexibility in setting rules. Thus, there was a great deal of heterogeneity across the U.S. States in the timing of welfare rule changes, and in the nature of the changes. See, e.g., Fang and Keane (2004) for an extensive discussion of these cross State differences in policies.

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

In this paper, our empirical work is guided by a structural model of mother's employment and child care decisions that we describe in section 4.1. Guided by this model, we obtain approximate decisions rules for employment and child care use, and estimate these jointly with the child's cognitive ability production function – an approach we refer to as "quasi-structural." In our selection model, welfare rules provide natural exclusion restrictions, as it is plausible that they enter the decision rules for employment and day care use, while not entering the child cognitive ability production function directly. Our results imply that if a mother works full-time, while placing a child in day care, for one full year, this reduces the child's cognitive ability test score by 3.0%, which is 0.135 standard deviations.[4]

The result we obtain here is very similar to what we obtained in Bernal and Keane (2005), where we adopted a single equation instrumental variable (IV) approach. There, our estimates implied that one year of full-time work and day care use would lower a child's test scores by 2.9%. 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 approach implements a selection correction (for the problem that arises because children who are placed in day care and/or having working mothers may differ systematically from children who are not) in a somewhat different way. Thus, it is comforting that results are so robust across the two approaches.

It is worth commenting on the relative merits of the IV vs. quasi-structural approaches, and of these vs. a fully structural approach, i.e., FIML estimation of the structural model of section 4.1 which we are attempting in ongoing work. One advantage of the quasi-structural approach is that, by explicitly estimating the work and child care decision rules, and by including the mother's wage function as part of the system, we achieve a rather substantial efficiency gain.

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[4] The coefficient on the coefficient capturing the effect of full-time quarterly work and day care use in the log test score equation is -.00747 with a standard error of .00048 (t = -15.56). This implies an effect of -.02988 for a full year. The standard deviation of log scores is .2204.

Indeed, the standard error on the cumulative childcare use coefficient in the log test score equation falls by a factor of 6, giving us much greater confidence in the estimated effect size.[5] This arises in part because the residual in the wage equation conveys information about the mother's unobserved skill endowment, and hence about the unobservable in the test score equation. On the other hand, misspecification of the joint distribution of the unobservables across the four equations of the system could lead to inconsistency.

One advantage of the single equation IV approach is its relative simplicity of implementation, which, in Bernal and Keane (2005) enabled us to examine a very large number of alternative specifications in which maternal work and day care use affects cognitive outcomes in different ways. For instance, it may be cumulative inputs that matter, analogous to the typical Mincer earnings specification where cumulative schooling and work experience affect current human capital, or it may be average inputs, or more recently inputs may matter more (or less). Or maternal work and day care may have larger effects if they occur at earlier or later child ages. Or, different types of day care, such as formal vs. informal, may have different impacts on child outcomes. In Bernal and Keane (2005) we were able to estimate a very large number of alternative specifications to examine these issues. Given the time required to estimate the quasi-structural system, such extensive testing would not be practical here.

A key difference between a fully structural approach and either the single equation IV or quasi-structural approach is this: FIML requires that the process by which agents form expectations of the forcing variables be fully specified. For instance, we could assume perfect foresight regarding future welfare rules, or myopia (i.e., each annual rule change comes as a surprise), or rational expectations (i.e., agents know the process generating the rules and form expectations accordingly), or something else. The IV and quasi-structural approaches allow us to sidestep this issue in estimation. This might superficially appear to be a clear advantage, but it imposes an important problem when one wishes to consider policy simulation. A change in welfare policy rules may have very different effects on maternal work and day care use, as well as on goods inputs into children, depending on the extent to which the change is perceived as permanent or transitory.[6] Thus, to simulate the effect of a welfare policy change on maternal decisions and child outcomes, we can't avoid making assumptions (either explicitly or

[5] Using linear IV, the coefficient is -.00741 with a standard error of .0029 (t = -2.56).
[6] See Keane and Wolpin (2001, 2005) for a detailed discussion of these issues.

implicitly) about expectations.[7]

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

Bernal's (2003) paper relied on very different exclusion restrictions from those used here. She treats the age profiles of husband and wife earnings as exogenous, in the sense that (1) only the parents skill endowments, and not their age, affects the skill endowment that the child inherits, and (2) only skill endowments and permanent income of mothers and husbands, and not short run fluctuations in household income (such as those generated by movement along the age path) affect the endowments they transmit to children, or their investment in children. Otherwise identical women who have children when they or their husbands are at different parts of the life-cycle age path will have different incentives to work. This creates exogenous variation in work incentives (uncorrelated with child ability endowments) that help to identify effects of maternal time inputs.[8] While we find this approach to identification appealing, we think the welfare policy rules we use here are more appealing, as their exogeneity is less subject to challenge.

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

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[7] More subtly, the perceived persistence of the actual welfare policy changes during the sample period may influence what the IV and quasi-structural estimates of maternal time effects actually 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. Then, the estimated effects of maternal time inputs may differ depending on the perceived persistence of the rule changes that induced them.

[8] Indeed, in the NLSY data Bernal (2003) 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).

2. Literature Review

A number of prior studies, mostly in the developmental psychology literature, have used NLSY data to assess the effect of maternal employment or child care use on children's cognitive development. Recent reviews of this literature can be found in Love, Schochet and Meckstroth (1996), Blau (1999), Lamb (1996), Haveman and Wolf (1994) and Ruhm (2002).[9] Less than half of these studies provide results that are interpretable in terms of effects of specific inputs.[10] Most of these studies present simple correlations between inputs and child outcomes and do not include additional controls for family characteristics and/or child characteristics. Furthermore, some of these studies use small samples, often nonrandomly selected. In most cases, no control for self-selection of children into child care arrangements (and/or the group of working mothers) was implemented.[11]

In Bernal and Keane (2005) we summarize the results reported in this literature, which are quite inconclusive. Of the papers that use the NLSY data to assess the effect of maternal employment on child cognitive outcomes, roughly a third report positive effects, a third report negative effects and the remaining report 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 use (and/or daycare quality) on children's outcomes,[12] estimated 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.

Reasons for the diversity of these results may include the wide range of specifications that are estimated, as well as the common limitation of failing to control for potential biases that may arise due to the endogeneity of employment and child-care choices. Only a handful of studies, which we discuss later, have tried to overcome the endogeneity problem by (1) using a very extensive set of control variables, (2) running child fixed effects models, and/or (3) using instrumental variables.

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[9] There are several papers, such as Todd and Wolpin (2003), Rosenzweig and Wolpin (1994), Rosenzweig and Schultz (1983), on the general topic of the specification/estimation of cognitive ability production functions. We summarize here only studies related in particular to the parental time and child care inputs.

[10] Some studies show associations between clusters of child care arrangements and children's development instead of assessing the impact of each input (Howes and Rubenstein (1985), Peterson and Peterson (1986), Studer (1992)). In some other cases, coefficient estimates or signs of the estimated effects are not provided by authors (e.g., Howes and Rubenstein (1981)).

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

[12] In this case we do not restrict ourselves to studies that use NLSY data only.

To make the exposition of the literature more clear, it is useful to have a specific framework in mind. Consider the following equation, interpretable as a cognitive ability production function:

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

where S_{ijt} is the child's cognitive outcome for child i of mother j at age t. Here, T_{ijt} is a measure of the maternal time inputs up through age t. This might be a scalar, as in a cumulative specification, or a specification where only average inputs or the current input matters. 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 used in the production of child's ability. Next, X_{ijt} is a set of controls for the child's initial skill endowment. This might include variables such as the mother's age, education, AFQT score, etc. (meant to capture the inherited ability endowment), and/or initial characteristics of the child such as gender, race, and birthweight. Turning to the error components, μ_j and δ_{ij} are family and child effects, which capture parts of the *unobserved* skill endowment of the child. Finally, ε_{ijt} is a transitory error term that may be interpreted as the measurement error inherent in the test plus any error in recording the test result.

While (1) is the general setup that, at least implicitly, seems to underlie most of the papers in the literature, none actually estimate this equation, and many estimate equations that seem quite far from it. One fundamental problem is that the maternal time input T and the goods inputs G are not directly observed. Most papers have ignored this problem, simply using maternal employment or child care use in place of maternal time.[13] Also, most papers use one of the other of these variables, and do not examine both. Similarly, most papers simply ignore G, while a few attempt to proxy for it using income of the mother or the HOME environment index (which measures not only physical characteristics of the household but also features of the parent-child relationship).[14] To our knowledge, only James-Burdumy (2005) discusses in detail

[13] For example, Vandell & Ramanan (1992) estimate the effect of maternal employment on child's 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] Baydar and Brooks-Gunn (1991) estimate the effects of both maternal employment and child care arrangements but do not include goods/services in the specification of the production function nor a proxy for these such as household income. Desai et al. (1989) estimate the effect of maternal employment on children's achievement and

the relationship between a child ability production function and her estimating equation by pointing out the difficulty in interpreting the coefficients in the latter when proxies are used for the maternal time and goods inputs in the cognitive ability production function.

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

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

Consider first the studies that could be classified as using extensive controls (like mother's AFQT), for the child's skill endowment. Among others, Han et al (2001), Baydar and Brooks-Gunn (1991), Parcel and Menaghan (1994), Vandell and Ramanan (1992) and Ruhm (2002), use an extensive set of observable characteristics of the child and the mother, which includes mother's AFQT score. In spite of this, the results of this group of papers are not conclusive. For example, Baydar and Brooks-Gunn (1991) report that maternal employment in the child's first year of life negatively affects cognitive outcomes while Vandell and Ramanan (1992) report positive effects of early maternal employment on math achievement and positive effects of current maternal employment on reading achievement. Ruhm (2002) finds significant negative effects of maternal employment on math scores while Parcel and Menaghan (1994) report small positive effects of maternal employment on child's cognitive outcomes.

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include the average number of child care arrangements during the first three years after birth and household income as additional controls without much discussion of whether these should be considered additional inputs or the implications in terms of the interpretation of the estimated coefficients of this particular specification.

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

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

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

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

[16] James-Burdumy (2005)'s fixed effects (FE) estimates in some cases imply large effects of maternal employment on scores. According to the results in Table 5, an increase in maternal work hours from 0 to 2000 in year 1 of the child's life would reduce the PIAT math score (measured at ages 3 to 5) by (-.00117)×2000 = -2.4 points. This is actually quite a bit larger than the effect we estimate for one year of full-time work (i.e., our estimates imply that about 3 ½ years of full-time work and day care use would lower test scores by a comparable amount). On the other hand, James-Burdumy (2005) finds no significant effect of maternal employment after the first year, so her estimate of the effect of five years of full-time employment is not large. The main difference between her results and our results in Bernal and Keane (2005) is that we find maternal time is more important in years 2+ than in year 1.

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

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

From our perspective, a key difficulty in interpreting the Blau and Duncan results is that their specifications makes it difficult to infer any estimate of the effect of maternal time per se. Both studies include the HOME environment index, which is constructed by combining about 30 survey items to form cognitive stimulation and emotional support indices. The 30 items include both goods inputs, like books in the home, and time inputs, like how often the child is read to, eats meals with the parents, or talks with the mother while she does housework. Thus, the coefficients on whether the mother works or uses day care measure the effect of those variables holding the HOME index fixed. In contrast, we are interested in the total impact of the maternal time input on child outcomes. This should include how a decline in the time input (resulting from increased work or day care use) affects time spent reading to the child and so on.

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

It appears that only two papers have attempted to use IV. These are Blau and Grossberg (1992) and James-Burdumy (2005). Both of these papers look at effects of maternal work on child outcomes, and do not examine effects of maternal day care use *per se*. More importantly, both papers suffer from the problem that the instruments are extremely weak. Thus, we would argue that their attempts to implement IV were not successful.

[18] In particular, a one-standard deviation in child care quality causes a .04 to .08 standard-deviation increment in child cognitive ability. Quality is assessed using the Observational Record of the Caregiver Environment (ORCE).
[19] Estimation of a first-differenced version of the value-added specification would eliminate the fixed effects, but Blau (1999) points out this is difficult or impossible due to limitations of existing data. This would require three outcome observations and two lagged input observations. Even if feasible, this approach would entail a severe efficiency loss.

For instance, Blau and Grossberg (1992) use work experience prior to childbirth as the instrument for maternal employment.[20] It is questionable whether this variable is uncorrelated with the child cognitive ability endowment (since it is likely to be correlated with the mother's cognitive ability endowment). But, setting that problem aside, note that the standard error of the variable for "proportion of weeks worked by the mother in the 2nd and later years of the child's life" increases from 1.864 to 26.831 when this instrument is used in place of running OLS (compare columns 1 and 2 of their Table 2). The latter figure implies that, to attain significance at the 5% level, the coefficient would need to be on the order of -53, implying that a mother shifting from no work to full-time work in the 2nd through 4th years would lower the PPVT test score by 53 points (the mean and standard deviation of the score are 91.18 and 18.06 respectively).

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

Clearly, in both these papers, the instruments are too weak for the IV estimators to identify plausibly sized effects of maternal employment on child outcomes. The main advantage of our approach is that the welfare policy instruments that we employ are much stronger. Indeed, in our companion paper Bernal and Keane (2005), we note that the first stage marginal R-squared values that we obtain using these instruments are quite large relative to what one typically sees in the IV literature (i.e., on the order of .05 to .10), and, in the second stage, standard errors on maternal employment and day care use do not "explode" when these instruments are used.

Finally, Bernal (2003) develops a model of work and child care choices of women after birth. Estimation of the child's cognitive ability production function - which includes mother's

[20] According to footnote 7 of their paper, this is the only variable in the prediction equation for maternal employment that does not also appear in the child outcome equation.

cumulative work and child care use (as well as cumulative income since childbirth) as inputs - jointly with the mother's work and child care decision rules enables her to implement a selection correction, in the sense that she can adjust for the fact that certain types of children are more likely to be put in child care and/or to have working mothers. Her results suggest that the effects of maternal employment and child care use on children's cognitive ability are rather sizeable. In particular, an additional year of working experience and child care use is associated with a reduction of approximately 2% in cognitive ability test scores of children ages 3 through 7.

Bernal restricted the sample to women that did not have an additional child for at least five years after birth. This enabled her to avoid modeling fertility decisions and mothers' time allocation among multiple preschool aged children. However, her results may not generalize to larger families. In our reduced form framework we let the effects of maternal work and day care depend on the number of children. Additionally, she relies on certain exclusion restrictions that may be debatable. Specifically, she assumes that short run movements in mothers' and husbands' wage rates enter the mother's working and child care decision rules, but do not directly affect child's ability (for example, movement along the mother's and father's age-wage profile generates exogenous variation in their wage rates, which in turn affects the mother's work and child care decisions but does not directly affect child outcomes). We believe that additional (and stronger) instruments are available for single mothers. In this paper, we propose to use the variation in welfare rules to achieve a stronger basis for identification.

3. Welfare Rules and their Effects on Work and Child Care Decisions

In this section we describe the most relevant changes in welfare rules and child care policy that occurred during the 90s, and discuss how these affected single mother's incentives to work and use child care. Between 1993 and 1996, 43 States were granted "Section 1115" Welfare Waivers which allowed them to adopt innovative approaches to welfare reform. Many of the policies adopted under State waivers were later incorporated into "The Personal Responsibility and Work Opportunity Reconciliation Act" (PRWORA) of 1996. PRWORA changed the welfare system into one requiring work in exchange for time-limited assistance. It created the Temporary Assistance for Needy Families (TANF) program, which replaced the Aid to Families with Dependent Children (AFDC), and created the Child Care and Development Fund (CCDF). Under TANF and the CCDF, States operate their own programs, so a great deal of heterogeneity in work incentives and day care subsidy programs across states has emerged.

The main changes in the welfare system under both Section 1115 Waivers and TANF that are relevant for our exercise could be grouped into the following categories: termination and work requirement time limits, earnings disregards, child care assistance and child support enforcement. States differ greatly in terms of the rules they have adopted in each of these dimensions. Thus, we can construct an extensive set of State and individual-specific welfare rules variables, which we then use as an important source of identification for the parameters in the cognitive ability production function.[21]

Using the collected welfare rules, together with detailed individual demographic variables, we constructed two types of variables. The first group contains individual level policy variables. These are constructed from the individual's demographic variables in conjunction with relevant policy variables. Since we have individual level data, we exploited every opportunity to tailor policy variables to the individuals based on their demographics (e.g., determining whether or not a woman could possibly be subject to time limits, given the age of youngest child and when her State of residence began the time limit clock). The second group of variables corresponds to State level policy variables. It includes all variables that vary across States and time, but do not vary across individuals in the same State and year.

In the following sections we outline the main aspects of the 1996 Welfare Reform and Section 1115 Welfare Waivers which are relevant to this work, in the sense that they generated plausible exogenous variation in work incentives, child care prices and availability. We discuss both the way in which we expect these rules to effect on work and child care decisions of single mothers, and how the policy variables were constructed and coded.

3.1. Time Limits

Under AFDC, single mothers with children under 18 were *entitled* to receive benefits, as long as they met the income and asset eligibility requirements. But under Section 1115 Waivers, and under TANF, the states could set time limits on benefit receipt. Indeed, PWRORA forbids States from using federal funds to provide benefits to adults beyond a 60-month lifetime time limit (except that 20 percent of a State's caseload can be exempted), and it allows states to set shorter time limits. However, States may use their own funds to aid families that have reached

[21] The various data sources used to construct the policy variables are discussed in Fang and Keane (2004).

the federal time limit. Thus, for instance, New York and Michigan do not impose termination time limits,[22] California imposes a 5-year time limit but at that point only the adult share of benefits is cut, and Texas and Florida impose termination time limits in the 2-3 year range.

We can think of the potential impact of time limits as falling in one of two types: anticipatory and direct effects. The latter are simply related to the fact that a welfare recipient who reaches the time limit becomes immediately ineligible for benefits (so long as the limit is being enforced). The former is associated with the more subtle idea that if an individual is forward-looking and is faced with a welfare time limit then she will try to "save" or "bank" months of eligibility, in order to use them when it is truly necessary.[23]

In this paper, we use several variables to capture the impact of time limits. These incorporate both time limits created under TANF and earlier under AFDC waivers. One set of variables will capture variations at the state level, while others are individual-specific in the sense that they capture whether a specific woman in the sample could potentially be subject to a given rule. These variables are summarized in Table 1. Each variable has up to three subscripts: *i* for individual, *s* for State and *t* for period (quarter in our case).

First, we include a dummy for whether the State of residence of a single mother had imposed a time limit (TLI_{st}) in time *t* and a variable that indicates the length of the time limit in state *s* at time *t* (TL_LENGTH_{st}). In addition, we include a dummy for whether the time limit could be binding for that particular woman (TL_HIT_{ist}). The latter is individual specific since it accounts for the age of this woman's children. In other words, a single mother whose oldest child is A^o years old cannot have received welfare for more than A^o years. This means that the time limit cannot bind for this woman unless A^o exceeds the limit, regardless of how many years ago her State implemented time limits.

Note that TLI_{st} captures an anticipatory effect of time limits, while TL_HIT_{ist} captures a direct effect. Some additional variables that capture anticipatory and direct effects of time limits on work decisions were constructed: First, a variable that we call "months elapsed since the

[22] These States have chosen to use State funds to provide benefits to families beyond the 60-month Federal limit.
[23] In a dynamic setting, a single mother should make welfare participation decisions by comparing the value of current period welfare benefits to the value of current period potential earnings plus the "option value" of conserving a month of benefit eligibility. Grogger and Michalopoulos (1999) point out that this option value is, *ceteris paribus*, an increasing function of the time horizon over which benefits may be used (the number of months/years until the woman's youngest child reaches 18) and a decreasing function of the stock of remaining months of eligibility. For instance, the option value of preserving a month of eligibility is greater when the woman has only one month left than when she has 60.

implementation of time limits" ($ELAPSED\_TL_{st}$). Second, a variable called "months elapsed since the time limits could first potentially bind" for a given woman ($ELAPSED\_TL\_HIT_{ist}$). Third, we constructed a variable that measures the length of the time horizon over which a woman will be categorically eligible for benefits, which can be thought of as increasing the option value of "banking" welfare eligibility. This is equal to the remaining time until her youngest child reaches age 18 ($REMAIN\_ELIG_{ist}$). Finally, as we mentioned before, the option value of "banking" welfare eligibility is decreasing in the stock of eligible months that a woman currently possesses. This measure is constructed by calculating the maximum number of months that a woman could have received welfare since her State started her clock and subtracting this from the State time limit. We call this variable $REMAIN\_TL\_ELIG_{ist}$. Finally, many States mitigate the impact of hitting a time limit by only deleting the adult portion of benefits (i.e., continuing the child portion). We indicate this feature by $DCHILDBEN_{st}$.

It is worth emphasizing that we assume the woman's demographics and the welfare policy rules she faces are exogenous. In order for our policy variables to be valid instruments we require that they be only functions of the demographic and policy variables. For example, we do not want to use a woman's actual welfare participation history to construct the remaining months on her time limit clock, because actual participation decisions are endogenous. Similarly, in constructing $REMAIN\_ELIG_{ist}$, we ignore the fact that a woman can always extend her months of categorical eligibility by having another child.

3.2. Work Requirements and Exemptions

Under PRWORA, with a few exceptions, recipients must participate in "work activities" as soon as job ready, or no later than two years after coming on assistance.[24] In FY 1997, each State had to ensure that 25 percent of all families in the state were engaged in work activities. This percentage increased to 50 percent in fiscal year 2002. Many States have chosen to adopt shorter work requirement time limit clocks. Under the first wave of TANF plans (adopted approximately from October 1996 to January 1998), 20 States required welfare recipients to start participating in work activities immediately. Under the second wave of revised TANF plans (roughly two years after the first wave), 25 States required immediate work participation. Of the

[24] "Work activities" include: 1) unsubsidized employment, 2) subsidized private sector employment, 3) subsidized public sector employment, 4) work experience, 5) on-the-job training, 6) job search and job readiness assistance, 7) community service programs, 8) vocational educational training, and 9) the provision of child care services to an individual who is participating in a community service program.

remaining States, most adopted the 24-month maximum allowed under the federal law.

Thus, due to variation in when States implemented their TANF plans, and in the length of their work requirement time clocks, there is substantial variation across States in how early single mothers could have been subject to binding work requirements. For example, work requirements adopted under AFDC waivers could have hit as early as mid-1994 in Iowa, October 1995 in Michigan, and mid-1996 in Wisconsin. Later TANF work requirements could have bind as early as the Fall of 1996 in Alabama, Connecticut, Florida, Oregon and Utah among a few other States. However, work requirements were not binding until December 1998 in New York or February 1999 in New Jersey.

Also, States have the option to exempt single parents with children up to 1 year of age from work requirements and have the flexibility to provide exemptions to other families. A few states only exempt single mothers with children under 3 or 6 months (e.g., California), while others chose to grant longer exemptions. Thus, within a State, there is variation across women in whether work requirements can be binding, based on age of the youngest child.

In order to capture these effects, we constructed the following variables. The first, $CHILD\_EXEM_{st}$ is a dummy variable that indicates whether state s has an age of youngest child exemption in place at t and AGE_$CHILD_EXEM_{st}$ is the age of youngest child below which a woman is exempt from work requirements. In addition, WR_HIT_{ist}, is an indicator for whether the woman could have been subject to work requirements. It is constructed based on when a work requirement could have first hit in State s, in conjunction with the age of the woman's youngest child and the State's age exemption.

Besides the age of youngest child exemption, many States allow a few other exemptions from work requirements under TANF. These include exemptions for single parents with children under age 6 who are unable to obtain child care, and for recipients who are disabled or have a disabled household member. Thus, we constructed an additional variable, $EXEMP_{st}$, for the total number of work requirement exemptions. Also, States also differ in the type of sanction imposed in case the recipient does not satisfy the work requirement. A "partial" sanction generally means that only the adult portion of benefits is taken away while the children's portion is not. In 1996, 9 States had imposed a full sanction. By 1997, the number of States with a full sanction increased to 23 and to 30 by 1998. The measure $WR\_ULT\_SANC_{st}$ is a dummy for whether State s imposes a full sanction. Both these variables can be thought of as measures of strictness with which States enforced work requirement time limits.

Finally, we include a dummy DWR_{st} for whether a State has a work requirement time limit in effect. This indicator captures the fact that, in principle, work requirements can also have anticipatory effects. If a State adopts a work requirement with a 24-month work time limit clock, this can create an incentive to avoid welfare participation even before the 24 months are used up. This could be done to preserve time on the clock, or just because the value of human capital investment today is increased given that expected future welfare participation is reduced. Two additional measures we include are WR_LENGTH_{st}, which is the length of the work requirement in months, and $ELAPSED\_WR_{st}$, which is the time elapsed since the work requirement was implemented. Lastly, we also constructed a variable called $ELAPSED\_WR\_HIT_{ist}$, which is the time elapsed since woman *I* may be potentially subject to work requirements.

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

AFDC/TANF benefits for eligible participants are, roughly speaking, determined by a formula in which a State specific grant level (or payment standard), which is an increasing function of number of children under 18, is reduced by some percentage of the recipient's income (net of work expense deductions). One variable we use to characterize the system is the maximum *potential* real monthly AFDC/TANF benefit, assuming zero earnings, constructed using the State payment standard for the corresponding family size of the single mother. We call this variable BEN_{ist}. We put this variable in real terms using a region-specific CPI.[25]

Under AFDC, benefits were reduced as income increased according to a "benefit reduction rate" that we denote BRR. This tax was applied after allowance for deductions for work and child care expenses. The deduction amounts and the BRR changed several times over the history of the program. In 1967, the BRR was decreased from 100% (i.e., a dollar-for-dollar reduction of benefits for each dollar of earnings net of deductions) to 67%. In 1982, it was increased back up to 100%. Since 1982, the work expense deduction was set at $90 per month, and there was an additional child care expense deduction. Under waivers and the TANF program, the BRR was made State specific, and it now varies considerably across States.

In addition, the AFDC program incorporated "earnings disregards" in an effort to

[25] BLS has computed the CPI from (or before) 1980 for 24 metropolitan areas. For individuals residing in one of these 24 metropolitan areas we deflated potential benefits by the corresponding CPI. The potential benefits of individuals in other areas were deflated using a region-specific (western, south, midwest and northeast) CPI.

encourage work among participants. That is, if a recipient started working, then for a period of time, a fraction of her earnings (on top of the amounts set aside for work and child care expenses) would not be subject to the BRR. Generally, the disregard consisted of a "flat" component (e.g., the first $30 of monthly earnings) and a "percentage" part (e.g., one-third of earnings beyond the flat part). Both were eliminated after a certain number of months of work.

Starting in late 1992, many states obtained waivers to increase the income disregard and hence, encourage work. Under PRWORA, States are not required to adopt any particular earned income disregards, so a great deal of State heterogeneity has emerged. A few States expanded disregards and allowed them to apply indefinitely. For example, starting in 1998, California set a "flat" disregard of $225 of month earnings and a "percentage" disregard of 50% of additional monthly earnings, with no phase-out of either over time. Flat disregards varied from $0 to $252 across states, while percentage disregards varied from 0% to 100%.

Clearly, earnings disregards and the BRR affect a woman's incentive to work and use child care directly, by shifting her budget constraint, in particular, her after-tax wage rate. Note that changes in an indefinite percentage disregard are equivalent to changes in the BRR, so we code both together in the variable $PERC\_DISREGARD_{st}$. Flat disregards are coded in $FLAT\_DISREGARD_{st}$.

3.4. Child Support Enforcement and Child Support Income

Child support is an important source of income for single women with dependent children, despite the widespread non-payment by non-custodial fathers.[26] Under AFDC, recipients were required to assign all child support collections, up to the amount of benefits they receive, to the welfare agency. States were required to pass-through the first $50 of current month child support payments to the family for which they were collected. The amount of this pass-through was disregarded, so families received this amount as additional income. It did not count against the recipients' income in determining their family's AFDC eligibility or the assistance grant amount. The remainder of the child support collected was shared between the state and the federal government to reimburse the cost of providing AFDC assistance. Between January 1993 and August 1996 states requested and received waivers of a number of provisions related to child support enforcement. The most common types of waivers included changes in the

[26] In 2002, child support accounted for approximately 6.5% of single mother's real incomes (March CPS).

pass-through amount, or allowing single mothers to keep child support payments. In case of the latter, they would be subject to certain disregards just like earned income.

Under TANF, recipients are still required to assign child support collections to the welfare agency. However, the $50 pass-through has been eliminated. States may still opt to pass-through some of the funds collected to the custodial family. States establish their own policy in terms of whether or not to disregard the pass-through. Clearly, by shifting a single mother's budget constraint, the way in which child support income is treated has an effect on the woman's incentives to work and/or use child care. At the same time, enhance pass-throughs or disregards may also increase the incentive to participate in welfare. To account for these effects we include measures of the flat and percentage disregards in the state of residence of a woman ($FLAT_DISREGARD_{st}$ and $PERC\_DISREGARD_{st}$) under both AFDC waivers and TANF.

Aside from these AFDC or TANF rules, child support income collection has also been affected by the Child Support Enforcement (CSE) program. This program was enacted in 1975 to address the problem of non-payment of child support by non-custodial parents. For instance, CSE has implemented programs to locate absent parents and establish paternity. CSE expenditures have significantly increased from $2.9 billion in 1996 to $5.1 billion in 2002. These expenditures are an important indication of how likely is a single women of collecting child support. We include a measure of State level CSE activity by taking the State CSE expenditure and dividing it by the State population of single mothers ($ENFORCE_{st}$). Variation across States and over time in CSE spending, provides two key sources of variation that identify the effects of child support enforcement expenditures on welfare participation and work.

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

In the late 1980s, several programs were created that expanded Federal support for child care. The Family Support Act (FSA) of 1988 created two programs, AFDC Child Care and Transitional Child Care (TCC). The first program funds child care services of AFDC families who are working or participating in an approved work, education, or training program. The second program funds care for families for up to 1 year after they leave AFDC to start working. In both cases, AFDC participation determined eligibility. The Omnibus Budget Reconciliation Act (OBRA) of 1990 created the At-Risk Child Care Program and the Child Care and Development Grant (CCDBG). The former funds care for working families who are "at risk" of becoming eligible for AFDC if they are not given child care assistance. The latter program provides subsidies to low-income working families generally. Unlike AFDC Child Care and TCC, these benefits were not an entitlement. Under PRWORA these four pre-existing programs were consolidated into the Child Care and Development Fund (CCDF). The CCDF is a block grant to states to provide subsidized child care programs for low-income families, including those who are not current or former cash assistance recipients. Under the CCDF, states have autonomy to design child care assistance programs for low-income families and a great deal of heterogeneity has emerged across States in the design of their child care subsidy programs. In particular, income eligibility criteria, reimbursement rate ceilings and parent co-payments (States may require a contribution from the family to the cost of child care) vary significantly across states. Additionally states differ in terms of whether they give priority to low-income families who are on TANF or just transitioning off TANF.

As an additional policy instrument, we use the State CCDF expenditure per single mother ($CHILDCARE_{st}$). This variable measures the availability and generosity of child care subsidies in a State. An alternative to measure the generosity of a State's child care program would be to use detailed program parameters, such as, monthly income eligibility criteria, reimbursement rate ceilings or the co-payment rates, which are State specific and have also varied over time. We opt not to use these measures due to problems associated with rationing. For example, a State with a seemingly generous program (e.g., high income eligibility threshold and low co-payment) will tend to have a longer waiting list. Hence, program generosity can be more accurately measured by the States' actual per-case expenditure.

3.6. Other Contemporaneous Policy Changes: The Earned Income Tax Credit

The Earned Income Tax Credit (EITC), enacted in 1975, is a refundable Federal income tax credit that supplements wages for low-income working families. Major expansions of the federal EITC occurred in 1986, 1991, 1994 and 1996. Because of these expansions, the number of families receiving EITC increased from 6.2 million in 1975 to 19.5 million in 2000 (U.S. House of Representatives Green Book 2000, pg 813).

The EITC rules specify four parameters, a "phase-in" and "phase-out" rate, and a "phase-in" and "phase-out" income range. These parameters depend on family size. After the expansions in the mid-1990s, the EITC became a sizable wage subsidy to low and moderate-income families. Thus, it may provide an important work incentive. For example, in 2003, the phase-in and phase-out rates for a family with one child are 34% and 15.98%, respectively. As of 2003, 17 States have enacted State earned income tax credits that supplement the federal credit.[27] To account for this effect we construct the EITC phase-in rate ($EITC_{ist}$) using Federal and State level EITC rules together with the mother's family composition.[28]

4. The Model

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

4.1. Overview of the Structural Model

Consider a woman who makes sequential choices about work, child-care and welfare participation in each period t following the birth of a child and until the child goes to primary school at age 5. For expositional convenience we will consider a woman who has a single child, and ignore additional fertility decisions (although we will allow for multiple children in the empirical work). In our model the time periods correspond to 3-month intervals. We allow for three work options (full-time, part-time or no work), while the child care and welfare choices are binary, so altogether there are 3·2·2=12 possible options in a woman's choice set. Of course, depending on the woman's state of residence and duration of welfare participation, this choice set will vary (e.g., a woman who resides in a state with a 24 month work requirement time limit and who has been on welfare for 24 months will no longer have the option of receiving welfare while not working, so her choice set size is reduced). Formally, we denote the choice set as:

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[27] We collect this information from Fang and Keane (2004).

[28] In addition to these policy variables, we also included several variables that measure local demand conditions in the set of instruments that we use as exclusion restrictions to help identify the selection model as these plausibly alter incentives of women to work and use day care but are not directly correlated with the child's ability. These variables are described in Table 1. In particular, we included the unemployment rate in the State of residence in period t, the average hourly wage rate at the 20th percentile of the wage distribution in the State of residence in period t and the percentage of the State of residence s labor foce employed in services in period t.

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

where h_t denotes hours of work (2=full-time, 1=part-time, 0=no work), g_t is an indicator for welfare participation, and I_t^c is an indicator for whether or not the woman utilizes child care in period t. We put a subscript for State (s) as well as time (t) on the choice set J_{st} to indicate that it may depend on both State of residence and time, due to cross State and cross-time variation in welfare rules, and the woman's prior history (e.g., duration of welfare receipt).

It will also be useful to define the choice indicator:

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

Next, we need to specify the current-period utility function given choice of option j. Following Bernal (2003), a reasonable functional form would be:

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

where the consumption c_t is given by the budget constraint:

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

The utility function in (2) has the common CRRA form in consumption, with parameter α_1. The parameter α_2 is the disutility from working. The variable A_t is cognitive ability of the child. This is generated by a production function that we will define below. The mother gets utility from the child's cognitive ability according to the CRRA function with parameter λ, as in Bernal (2003). She estimated that $\lambda<1$, which implies that mothers get diminishing marginal utility from child ability, and will therefore have an incentive to engage in behaviors that compensate children with relatively low initial ability endowments.

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

The α_5 through α_9 terms in the utility function capture various aspects of the utility/disutility from child-care use. These terms are patterned after those in Bernal (2003), who found that all of them are necessary, if one wants to fit the data on child care utilization well. The parameter α_5 is a general non-pecuniary benefit/cost associated with the use of child-care. The parameter α_6 is an extra disutility from working if child-care is not available. The parameter α_7 is an extra cost of initiating child-care if you haven't used it before. This may capture the search time cost of finding a daycare center, and/or the psychic cost of first time separation from the child. The parameter α_8 is an extra cost from using child-care during the first quarter after birth (t=1), and α_9 is an extra cost from using child-care before the child is one year old (t<5). Both of these parameters capture the fact that it is more difficult to find day care centers that will take infants, and that infant care is generally more expensive, along with the fact that the psychic cost of separation from the child is greater when the child is very young.

Finally, ε_t^j is an alternative-specific random taste shock. In order to capture the fact that some alternatives are more similar than others, it would be necessary to allow these terms to be correlated across alternatives. FIML estimation of the model would require us to make a distributional assumption on these stochastic terms.[29] For example, we could assume they are multivariate normal and independent over time.

Turning to the budget constraint (3), note that 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 work as 500 hours. This sort of grouping of hours facilitates estimation, since it keeps the choice set purely discrete. Keane and Moffitt (1998) adopted the same approach in their joint modeling of labor supply and welfare program participation. They argued that grouping was desirable because hours are very concentrated at 20 and 40 per week, and because much of the variation away from those figures is likely to be measurement error. They also found that their results were not very sensitive to how hours are grouped. The next term in the budget constraint, N_t, denotes non-labor income. This may include child support payments.

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

[29] Note that a distribution assumption is necessary not only to form the likelihood function, but also to solve the agent's dynamic optimization problem.

benefit rules parameters π_{st}.[30] Under TANF and section 1115 waivers, there is a great deal of heterogeneity across states in the rate at which welfare benefits are reduced if the woman has earned or unearned income. The duration of prior welfare participation matters for benefits because some states eliminate or reduce the benefit by some proportion when a critical level of duration is reached (e.g., in California the benefit is reduced, but not eliminated, after 5 years). Such features are captured in π_{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 the state child-care subsidy programs funded by the CCDF, the required co-pay levels for day care depend on the woman's earned and unearned income levels. In addition, in many states TANF participants (g_t=1) are not required to make co-pays. The vector θ_{st} captures how co-pay and eligibility requirements vary across states.

Aside from the budget constraint, a woman faces two other constraints that influence her work and child-care utilization decisions: her wage function and the child cognitive ability production function. In order to explain these, it is useful to first define w_o as the "initial wage" of the woman, prior to giving birth. Note that this would be the actual wage for an employed woman, or a latent offer wage based on latent earnings capacity for a non-working woman. We model the initial wage as a function of a vector X_o of observable characteristics that include education, age, age squared, race and the mother's AFQT score. Thus, we have

$$\ln w_o(\mu_w) = \mu_w + \theta_1 educ + \theta_2 age + \theta_3 age^2 + \theta_4 race + \theta_5 AFQT + v_{wo}$$

where μ_w represents *unobserved* heterogeneity in the mother's skill endowment. The variables *educ*, *race* and *AFQT* capture *observed* heterogeneity in the skill endowment, while *age* (the woman's age at the time of child birth) captures movement along the life-cycle wage path for a woman of a given skill endowment. Finally, v_{w0} captures transitory shocks to income and/or measurement error, which we assume are serially independent. FIML would require a distributional assumption on v_{w0}, such as $v_{w0} \sim N(0, \sigma_w^2)$.

It will 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:

[30] 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.

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

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

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

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

Here, $\mu_s \equiv (\rho\mu_w + \mu_k)$ represents unobserved heterogeneity in the child's cognitive ability endowment. This consists of a part $\rho\mu_w$ that is correlated with the unobserved part of the mother's ability 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: the mother's AFQT score (*AFQT*), *educ, race,*[31] total work experience before giving birth (*EXPBEF*), and an indicator for whether the mother was working during the year prior to giving birth (*I*[*worked bef*]). We also include indicators for whether the mother was less than 20 or over 33 at the time of childbirth (*I*[*age<20*] and *I*[*age>33*]). Finally, there is a part of the endowment that is correlated with observed characteristics of the child, although the only such observables we have are birthweight (*BW*) and *gender*, a dummy variable indicating if the child is female.

We include the age indicators in (5) because there is some evidence that teenage mothers (and older mothers) have less healthy children (i.e., there may be a direct physiological adverse

[31] Race is a dummy variable that equals 1 if the child is non-white, 0 otherwise.

affect), although some evidence also suggests that this association vanishes if one controls for mother's characteristics like education and income.[32] Beyond that, we think it is plausible to assume, like Bernal (2003), that age of the mother does not directly affect the cognitive ability endowment that she transmits to the child. However, we will experiment with different specifications of (5), and in particular test for significance of additional age effects.

It is important to emphasize that the coefficients γ_1 through γ_9 in (5) do not capture causal affects, but merely *correlation* between observables and the child's cognitive ability endowment. It is desirable to let observables "sop up" as much as the child unobserved ability endowment as possible, as this should reduce the sensitivity of our results to the distribution assumptions we make 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 procedure used to estimate the effect of maternal time, whether it be single equation IV, quasi-structural estimation, or FIML estimation of the fully specified structural model.

Finally, we turn to the cognitive ability production function itself. This function captures the notion that the child's initial cognitive ability endowment, A_o, interacts with subsequent inputs maternal time (T), child care inputs (C) and goods (G) inputs 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 explicity, and in which only cumulative inputs matter (although we relax this in the empirical work reported below).[33] Dropping the mother and child subscripts, we have:

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

Here, T_t denotes the cumulative input of maternal time through age t, C_t denotes the cumulative input of alternative care givers' time, and G_t denotes the cumulative input of goods. It is convenient to let goods enter in log form, for reasons that will become clear shortly. Note that, comparing (1) with (6), The term $\alpha_4 X_t + \mu + \delta$ (i.e., the observed and unobserved parts of the

[32] See, for example, Lopez (2003) and Geronimus (1994).

[33] A completely general form of the function, in which inputs at age t have a potentially different effect on ability at each age t', and in which the ability endowment μ_s has a potentially different effect on ability at each age, is not feasible due to proliferation of parameters. We adopt a simplification, familiar from the human capital literature, and we assume that: (i) only cumulative inputs matter, rather than their timing, and (ii) that the effect of the permanent unobservable is constant over time (e.g., in the standard Mincer earnings function, only cumulative education and experience are assumed to affect human capital, and the unobserved skill endowment is typically assumed to have a constant effect on log earnings).

ability endowment) has been subsumed in ln $A_o(\mu_s)$. Finally, we drop ε because the dependent variable in (6) is the actual ability rather than a noisy test score measurement.

Now, given that T and G are not directly observed, we need to make some further assumptions that relate them to observables in order to obtain an estimable equation. Consider first the measurement of the maternal time input. One could imagine a model where mothers decide how much "quality" time to devote to the child while at home (e.g., children's time is divided between day-care, "quality" time with the mother, and time spent sitting in front of the TV while at home with the mother). Given that we don't observe actual contact time between mothers and children (let alone the subset of this that is "quality" time),[34] we simply side-step the issue by assuming that $T_{it} = T\text{-}C_{it}$, where T is total time in a period. Thus, we distinguish between only two types of time (i.e., time with the mother and time in child-care). This means we can rewrite (6) as:

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

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

Next, we turn to the fact that the goods inputs G are, to a great extent, unobserved. For example, the NLSY contains information on number of books in the home, but lacks other potentially important goods inputs like nutrition, health care, tutors, recreation, etc.. To deal with this, consider a specification where the decision rule for cumulative monetary investment (in the form of goods) in the child's ability (conditional on work, income and child-care usage decisions) up through age t is given (approximately) by:

$$\ln G_t = \pi_0 + \pi_1\mu_w + \pi_2\mu_s + \pi_3 C_t + \pi_4 \ln I_t + \pi_5 t + \varepsilon^g . \qquad (8)$$

In (8) cumulative investment may depend on the mother's skill endowment μ_w for two distinct reasons: (i) μ_w affects permanent income and (ii) μ_w affects tastes for child cognitive ability. The child's cognitive ability endowment μ_s also matters, because it may affect the mother's returns to investment in child ability (see (2)). Cumulative child care time C_t enters (8) because, if child-

[34] As we discussed in section 2, the NLSY does contain information on such variables as how often the child is read to, eats meals with the parents, or talks with the mother while she does housework. But it is difficult to see how to use these to construct a single measure of the total maternal time input itself.

care time does affect child ability, then mothers may attempt to compensate for these effects by altering goods inputs.

Cumulative income since birth of the child, I_t, enters (8) to the extent that short run fluctuations in income affect investment in children. This occurs both because (i) short run fluctuations in income do affect permanent income – although this effect should be small, and (ii), there may be liquidity constraints. Finally, equation (8) also contains a time effect (i.e., cumulative goods investment grows with age) and a stochastic term ε^g. This stochastic term captures the mother's idiosyncratic tastes for investment in the form of goods. This could arise due to heterogeneous preferences for child quality.

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

$$\begin{aligned}
\ln A_t(\mu_s) &= \ln A_0(\mu_s) + (\gamma_{11}T)\cdot t + (\gamma_{12}-\gamma_{11})C_t \\
&\quad + \gamma_{13}[\pi_0 + \pi_1\mu_w + \pi_2\mu_s + \pi_3 C_t + \pi_4 \ln I_t + \pi_5 t + \varepsilon^g] \\
&= \gamma_{13}\pi_0 + (\gamma_{11}T + \gamma_{13}\pi_5)\cdot t + (\gamma_{12}-\gamma_{11}+\gamma_{13}\pi_3)C_t \\
&\quad + \gamma_{13}\pi_4 \ln I_t + X\gamma + (1+\gamma_{13}\pi_2)\mu_s + \gamma_{13}\varepsilon^g \qquad (9) \\
&= \beta_0 + \beta_1\cdot t + \beta_2 C_t + \beta_3 \ln I_t + X\gamma + \hat{\mu}_s + \hat{\varepsilon}^g
\end{aligned}$$

Equation (9) is estimable, because all the independent variables are observable. However, we must be careful about the appropriate estimation method and the interpretation of the estimates. As we have discussed at length, child care utilization may be correlated with the unobserved part of the child's ability endowment μ_s. In addition, child care use may also be correlated with ε^g, the unobserved taste shifter in equation (8), if tastes for child care usage are correlated with tastes for goods investment in children, as seems plausible.[35] To our knowledge, it has not been previously noted that consistent estimation of an equation like (9) requires instruments that are not only uncorrelated with the unobserved part of the child's skill endowment, μ_s, but also with the mother's tastes for goods investment in the child, ε^g. It seems plausible that the welfare rule parameters do satisfy this requirement.

[35] For instance, a mother with a high taste for child quality may both spend more time with the child (i.e., use less day care) and invest more in the child in the form of goods. This would tend to bias estimated effects of day care usage in a negative direction, since not only the maternal time input but also the goods input is lower for children in day care. Of course, the correlation could go the other way as well.

The cumulative income variable in (9) is also potentially endogenous, for multiple reasons. First, income depends on the jointly made child care use and work decisions. Hence it is potentially correlated with child ability for the same reasons as were operative for child care usage. Second, income depends on the mother's wage rate, which depends on her unobserved ability endowment. To the extent that this is correlated with the child ability endowment (i.e., $\rho \neq 0$ in (5)), this will also generate correlation between the mother's income and μ_s. Thus, we need to instrument for mother's income as well. Again, we will argue that the welfare rules R_{it} provide a plausibly valid instrument, since they should have important effects on work decisions, yet it is plausible that they are uncorrelated with child ability endowments.

Assuming that single equation IV or a quasi-structural approach using the welfare rules as exclusion restrictions provides consistent estimates of (9), it is important to recognize that the child care "effect" that is estimated is $\beta_2 = \gamma_{12} - \gamma_{11} + \gamma_{13} \cdot \pi_3$. This is the effect of child care time (γ_{12}) relative to the effect of mother's time (γ_{11}) plus the effect of any change in goods inputs that the mother may choose as a result 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 tell us how a policy like child care subsidies would affect child cognitive ability outcomes. Such subsidies would not only alter day care use, but also goods inputs, and 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 (6), the parameter π_3 comes from the decision rule for goods inputs (8), which is not policy invariant.

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

While we have considered particular functional forms in order to clarify the estimation issues, we will consider several variants of these in our empirical work. For instance, interaction terms between the child's initial ability and household inputs are included in order to allow the effect of inputs to vary depending on the type of the child.[36] In particular, Bernal (2003) found that the returns to maternal time in the 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 has available a set of cognitive ability test scores from which one has to infer it. Let S_t be 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) which capture the fact that the means on the different tests differ. The term v_{st} represents measurement error, which, for instance we could assume is distributed normally $v_{st} \sim N(0,\sigma_v^2)$.

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

A key issue that has to be addressed in structural estimation is what to assume that mother's know, because this importantly affects how the dynamic optimization problem is solved. For instance, in a similar model, Bernal (2003) assumes that mother's know the cognitive ability endowment μ_s of their child. On the other hand, it is not observed by the econometrician. While the assumption that mothers know more than econometricians is reasonable, the assumption that they have complete information may be extreme. Hence one might want to

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

consider alternative formulations where μ_s is split up into a component the mother observes and a component she does not observe. Again, explicit assumptions on this issue can be avoided in IV or quasi-structural estimation, but proper estimation methods and interpretation of results will depend on ones assumptions. [37]

We must also make an assumption 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: (1) mothers know how their decisions about working after childbirth will affect the depreciation of their market wages, or, in other words, the evolution of their human capital, according to equation (4), (2) they know how their decisions about work and child care use will affect cognitive ability outcomes for their child (as determined by equation (9)), and (3) they know how welfare participation decisions will 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.[38] Thus, the strict exogeneity assumption of the fixed effects estimator is violated.

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

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[37] For example, OLS and sibling fixed effects estimators implicitly assume that mothers do know the cognitive ability endowments of their children. If mothers do know μ_s, it creates an important potential source of bias in 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 by use of sibling fixed effects estimators, because, if mothers can see the endowment differences across their children they may treat them differently.

[38] This will true so long as work and day care decisions depend on perceived child ability. To be concrete, suppose that mothers try to 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 of first-difference estimators, this induces a negative bias in estimates of effects of maternal time on child outcomes (i.e., from t to t+1 the test score will tend to rise, while maternal work and day care use fall).

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

In addition, each individual woman has a set of individual specific state variables that stay fixed over time, or that we assume evolve exogenously. These include her skill endowment and her child's cognitive ability endowment, her race and education, the non-labor income she receives, and the state specific welfare and child care subsidy parameters she faces. As result of these variables, each woman faces her own unique optimization problem.[39]

Another issue that must be addressed is that a mother's choice problem changes fundamentally when the child reaches roughly age 5, at which point he/she can begin kindergarten or primary school. At that point there are no more decisions to be made regarding day care utilization (although after school care is still an issue). One strategy is to avoid modeling decisions beyond the time horizon of interest. For instance, Bernal (2003) models the mother's decisions from *t*=1, the first quarter after the child is born, until T=20. At T=21, she assume a terminal value function that is a flexible function of the values of the state variables at that point. In the present case, we could write $V_{T+1}(\Omega_{T+1}) = P(A_{T+1}, E_{T+1}, D_{T+1})$ 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).

FIML estimation of this structural model requires that, and any given trial parameter vector, we solve an agent's dynamic optimization problem numerically by "backsolving" from T=21 to t=1. Then, we can form the joint probabilities of observed choices, wages and test scores

[39] However, in describing an individual woman's optimization problem, we could suppress these variables in the notation, and focus only on the endogenously evolving state variables in Ω_t.

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. The Approximate Solution of the Structural Model

An alternative way of estimating the effect of mother's employment and child care decisions on the child's cognitive ability is to form approximations to the decision rules for work and day care implied by the structural model, and to estimate these jointly with a cognitive ability production function and a wage equation. We now briefly describe the specification of these equations. Consider first a linear approximation to the work decision rule implied by our structural model. We assume the value function for full-time work can be approximated as:

$$\begin{aligned} V_{f,t}^{*} &= \beta_o + \beta_1 age + \beta_2 age^2 + \beta_3 educ + \beta_4 race + \beta_5 AFQT + \beta_6 p_{t-1} + \beta_7 f_{t-1} + \beta_8 C_t + \\ &\quad \beta_9 D_t + \beta_{10} t + \beta_{11} BW + \beta_{12} gender + \beta_{13} I[age < 20] + \beta_{14} I[age \geq 33] + \beta_{15} I[C_t = 0] \\ &\quad + \beta_{16} I[t = 1] + \beta_{17} I[t < 5] + \overline{\beta}_{18} \pi_{st} + \overline{\beta}_{19} \theta_{st} + \varepsilon_{ft}^{*} \end{aligned} \quad (11)$$

In this equation, the latent index V_f^* that determines the decision whether to work full-time is written as a linear function of <u>all</u> the state variables in our model. Note that $\overline{\beta}_{18}$ and $\overline{\beta}_{19}$ are vectors of parameters that multiply the state and time specific welfare and child care subsidy rule parameters, π_{st} and θ_{st}. Finally we let $\varepsilon_{ft}^{*} = \mu_f + v_{ft}$.

The linear approximation to the part-time work value function rule will be identical except it will be associated to an alternative-specific stochastic term $\varepsilon_{pt}^{*} = \mu_p + v_{pt}$ and coefficients that go from β_{20} to β_{39}. 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 model. In forming the likelihood function, we simulate the multinomial probit choice probabilities using the GHK probability simulator (see Keane (1994)).

The child care decision rule is constructed in a similar way, by approximating the value function for use of child care by a linear function of all the State variables in the model (with associated coefficients β_{40} to β_{59} and a specific random shock ε_{ct}^{*}). We normalize the value function associated with no child care to 0, and assume that ε_{ct}^{*} has a standard normal distribution, so that this part of the model is a probit equation.

Next, we write the cognitive ability production function:

$$\begin{aligned} ln\, S_t &= ln\, A_o(\mu_s) + \beta_{60} C_t + \beta_{61}(C_t \cdot ln\, A_o(\mu_s)) + \beta_{62} I_t + \beta_{63}(I_t \cdot ln\, A_o(\mu_s)) \\ &\quad + \beta_{64} \cdot t + \beta_{65} d_{1t} + \beta_{66} d_{2t} + v_{st} \end{aligned} \tag{12}$$

where

$$\begin{aligned} ln\, A_o(\mu_s) = \beta_{67} + \beta_{68} AFQT + \beta_{69} educ + \beta_{70} race + \beta_{71} BW + \beta_{72} I[age < 20] + \\ \beta_{73} I[age > 33] + \beta_{74} gender + \beta_{75} EXPBEF + \beta_{76} I[worked\ bef] + \mu_s \end{aligned}$$

where $\varepsilon^*_{st} = \mu_s + v_{st}$. Recall that A_o is the child's initial skill endowment and d_1 and d_2 are test dummies (i.e., PPVT or PIAT-Math). Note that (12) includes interaction terms between the inputs and the ability endowment that we mention in section 4.1 but did not include explicitly in equations (9)-(10).

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

$$ln\, w_0 = \beta_{77} + \beta_{78} educ + \beta_{79} age + \beta_{80} age^2 + \beta_{81} race + \beta_{82} AFQT + \varepsilon^*_{w0}$$

and

$$\begin{aligned} ln\, w_t &= \beta_{77} + \beta_{78} educ + \beta_{79} age + \beta_{80} age^2 + \beta_{81} race + \beta_{82} AFQT + \beta_{83} \cdot t \\ &\quad + \beta_{84} E_t + \beta_{85} f_{t-1} + \beta_{86} p_{t-1} + \beta_{87}(E_t \cdot educ) + \varepsilon^*_{wt} \end{aligned} \tag{13}$$

We let $\varepsilon^*_{wt} = \mu_w + v_{wt}$ and assume that $\{\mu_f, \mu_p, \mu_c, \mu_s, \mu_w\}$ have a joint normal distribution F(μ). The fact that the time invariant unobservables in the 4 equations of the system (i.e., the multinomial probit for work, the probit for child care, the test score equation and the wage equation) are allowed to be correlated is the mechanism through which joint estimation of the whole system 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. Most critically, note that the state and time specific welfare and child care subsidy rule parameters π_{st} and θ_{st} enter the decision rules for work and day care utilization, but they do not enter the cognitive ability production function.

In constructing the welfare and child care subsidy rule parameters π_{st} and θ_{st} we assume that the woman's demographics and the welfare policy rules she faces are exogenous. In order for our policy variables to be valid exclusion restrictions we require that they be only functions of the demographic and policy variables. For example, we do not want to use a woman's actual welfare participation history to construct the remaining months on her time limit clock, because actual participation decisions are endogenous.

Note that high and low skilled women both face the same welfare rules, hence they cannot be correlated with individual characteristics. Unless, for instance, high skilled women tend to live in States with stricter rules or States which moved first towards welfare reform[40]. In Appendix 3 we present pre-reform average scores by States depending on whether the State implemented a Welfare Waiver prior to 1996 and whether they implemented stricter rules after 1996. As can be noted there is no significant difference in average test scores depending on what type of States we refer to. In fact, it seems that the States with higher average scores were more likely to adopt waivers or to have stricter rules. This is opposite to the bias one would worry about.

An alternative to estimating the quasi-structural dynamic selection model described here would be the even simpler single equation IV approach. That is, we could estimate the cognitive ability production function alone, using instruments for cumulative income (I_t) and child care use (C_t). These instruments should measure the average incentives to work and use day care over the period up until time t. This means somehow averaging the welfare and child care subsidy rule parameters over the period from the birth of the child up until time t. We have experimented with doing this in a few different ways, as we discuss below.[41]

Finally, we note that in these simpler non-structural approaches, it is feasible to use data on women with multiple children. We could then include the main effect of number of children in the test score equation, as well as interacting I_t and C_t with number of children to account for the issue that household income and day care use may affect child outcomes differently depending on the number of children (see the discussion in section 4.1). Prior non-structural work in this area has generally not discussed this issue. Also, note that number of children may itself be endogenous in such an equation (e.g., if there is a quality/quantity tradeoff). Welfare rule parameters are again used as instruments here. A related point is that prior non-structural work has generally included married and single women in the same sample when estimating

[40] States that approved Welfare Waivers prior to the 1996 Reform.
[41] See also Bernal and Keane (2005) for further discussion.

effects of maternal time or day care on child outcomes. Clearly, the assumption that marital status does not substantially alter the relationships of interest is quite strong.

5. The NLSY Data

5.1. Individual Data

We use data from the National Longitudinal Survey of Youth. The NLSY (1979 youth cohort) consists of 12,686 individuals, approximately half of them women, who were 14-21 years of age as of January 1, 1979. The sample consists of a core random sample and an oversample of blacks, Hispanics, poor whites and the military. Interviews were first conducted in 1979 and have been conducted annually to the present. On a regular basis, the NLSY79 has collected pre- and postnatal care information from the sample of women as they became mothers. Using data from the NLSY 79 Workhistory File, it is possible to construct a detailed employment history for each mother in the sample for the period surrounding the birth of her child, i.e., up to four quarters before birth and each quarter interval since the child's birth for a period of five years.

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

Unfortunately for our purposes, the NLSY does not report the actual number of hours that a child was in child care rather than in the mother's care. The child care variable available in the NLSY is simply an indicator for whether the mother used child care for at least 10 hours per week during the last month. This information in itself is not adequate to determine whether a child was in child care full-time or only part-time. However, by combining the child care variable with maternal work history information, we can make a reasonable determination about whether child care was full or only part-time. We describe how we do this in more detail in section 5.2.

In 1986 a separate survey of all children born to NLSY79 female respondents began. The child survey includes assessments of each child as well as additional demographic and development information collected from either the mother or the child. A battery of child cognitive, socio-emotional, and psychological well-being questions have been administered biennially for children of appropriate age.

Finally we use the geocode data that allows us to identify the residence state of each individual in order to be able to model the effect of state-specific welfare benefits and rules. Different rules imply different budget constraints and choice sets which the individual will face when deciding on work and child care.

Estimation of the quasi-structural model of section 4.2 requires a sample of women that are single (i.e., who do not cohabitate with a male co-resident) during five years following the birth of the child, and for whom we observe at least one child test score. There are 1,464 mothers in the NLSY that satisfy these requirements. Of these women, 245 had children between 1990 and 2000, so they are impacted by welfare waivers and TANF. Much of our leverage for identification will come from comparing behavior and outcomes of these 245 women with those for the 1,219 women whose children were born earlier, since these two groups are subject to very different welfare rules.

In Table 2 we present mean characteristics of the mothers in the sample compared with characteristics of all women in the NLSY. The women in our sample are younger than the average mother in the NLSY by less than a year and are also less educated, but only by around 4 months. A considerable percentage of mothers in our sample (83%) are Hispanic or black, while this proportion is 47% in the NLSY. Approximately 39% of women in our sample worked at some point during the first year after giving birth compared to 47% in the NLSY sample. The hourly wage before birth was lower for women in the sample and equal to $4.39 (constant dollars of 1983).

Figure 1 displays employment and child care choices after birth for the women in our sample. During the first quarter after birth, about 63% of single mothers stayed at home and did not use child care, 16% returned to work full time and 7% part-time while using child care. Around 13% stayed at home and used child care. By the end of the third year after birth, 36% of women were working full-time (and used child care) and 27% continued to stay at home and did not use child care and 18% stayed at home while using child care.

5.2. Maternal Time Inputs, Income and Child Assessments

A crucial point is that we do not directly observe the amount of time that a child is in child care rather than in the care of the mother. That is, the NLSY reports a dichotomous variable for whether a child was in child care for at least 10 hours per week or not during the last month, but it does not report the actual number of hours of non-maternal care. This information in itself is not adequate to determine whether a child was in child care full-time or only part-time. However, by combining the child care variable with maternal work history information, we can make a reasonable determination about whether child care was full or only part-time. Thus, we use the child care variables, in conjunction with the work history data, to construct: (i) a dichotomous indicator of child care use for purposes of estimating the child care probit, and (ii) a more refined measure of whether the mother used full-time, part-time or no child care, which we use to construct the child care usage measure C_t that appears in the cognitive ability production function (12).

Specifically, if a woman reported having used at least 10 hours per week of some kind of child care[42] then she is assumed to have used child care during the corresponding period. In addition, women reporting between 75 and 375 hours of work per quarter are assumed to be working part-time, women reporting more than 375 hours of work per quarter are assumed to be working full-time and women reporting less than 75 hours per quarter are assumed to be staying at home during the period. We define the following indicator function:

$$I_t^c = \begin{cases} 1 & \text{if mother works full-time and used child care} \\ 0.5 & \text{if mother works part-time and used child care} \\ 0.5 & \text{if mother did not work and used child care} \\ 0 & \text{otherwise} \end{cases} \qquad (14)$$

We adopt this definition in place of a dichotomous child care indicator of the NLSY in order to better capture the amount of time that the child is separated from the mother. Cumulative child care (C_t) is then constructed as $C_t = \sum_{\tau=1}^{t} I_\tau^c$, where t is the age of the child.

The logic of (14) is that, if a woman worked full-time, then her child care use must have been full-time, so we assign $I^c = 1$ in that case. On the other hand, if the mother did not work at all but still reported using child care, it seems highly likely that the child care usage was only part-time. We admit that proper assignment of the "mother worked part-time and used child

[42] Types of child care include care by a relative or non-relative, day care center, nursery/preschool or regular school.

care" category is not so obvious. However, changing this category from 0.5 to 1.0 had little effect on the results.

Finally, total real household income refers to reported income from all sources including wages, public assistance, unemployment benefits, interest or dividends, pension, rentals, alimony, child support and/or transfers from family or relatives. Household income is deflated using a region-specific CPI just as we did in the case of maximum real potential welfare benefits to account for differences in costs of living across metropolitan areas. As in the case of child care use, we have experimented with different specifications using cumulative annual real household income (since childbirth), average annual real household income and current real household income.

We use as measures of the child's cognitive ability the scores on the Peabody Picture Vocabulary Test (PPVT) at age 3, 4 and 5, and the Peabody Individual Achievement Test Reading Recognition subtest (PIAT-R) and Mathematics subtest (PIAT-M) at age 5 and 6. Both assessments are among the most widely used for preschool and early school-aged children. The PPVT is a vocabulary test for standard American English and provides a quick estimate of verbal ability and scholastic aptitude. The PIAT-M measures attainment in mathematics. It consists of eighty-four multiple-choice items of increasing difficulty. It begins with such early skills as numeral recognition and progresses to measuring advanced concepts in geometry and trigonometry. Finally the PIAT-R measures word recognition and pronunciation ability.[43]

6. Estimation Results

In Table 3 we present means and standard errors of the variables used in the estimation of the model. For example, the average log (test score) in the sample is 4.50 with a standard deviation of 0.22. 64% of women in the sample worked prior to giving birth at an average hourly wage rate of $4.39 (1983 dollars). On average, women in the sample had worked 4.7 years prior to childbirth and 72% of women had never been married. Average annual real household income is $10.9 thousand (1983) dollars. Finally, the total number of quarters that mothers used child care in this sample is 7.1 on average and child care was used 37% of the time (up to the date of the test) on average.

[43] In Appendix 2 we present a brief description of these three cognitive ability tests.

6.1. Estimation Results for the Quasi-Structural Model

In this section, we present results of the approximate solution of the structural model presented in Sections 4.2 and 4.3. The estimation procedure involves estimation of approximate decision rules for work and child care use, estimated jointly with the child's cognitive ability production function and the mother's wage functions, which are guided by the structural model outlined in Section 4.2. This "quasi-structural" version of the model (as we refer to this approach) is estimated by maximizing the likelihood function given by the approximate decision rules like equation (12) and the associated test score and wage density functions implied by equations (13) and (14).

In Table 4 we present estimates of the cognitive ability production function in equation (13) by several estimation methods. Columns (1) and (2) present OLS and RE estimates respectively. Columns (3) and (4) present IV estimates in which the welfare and child care subsidy rules in Table 1 are used as instrumental variables. In column (3) we assume that the effects of welfare rules on the endogenous variables are the same in every year after birth. Column (4), on the other hand, relaxes this assumptions and allows yearly welfare variables to have different effects on child care use and household income. Finally, column (5) presents the estimates obtained from our "quasi-structural"estimation by maximum likelihood.

First, note that OLS estimates of the effect of child care on children's achievement are indeed upwardly biased as we expected. Once we use instrumental variables or estimate a quasi-structural version of our model, the effect of child care declines with respect to the OLS estimates. The effect of child care use is negative and statistically significant. The magnitude of the effect is quite stable across different methods that implement selection corrections (IV and our quasi-structural estimation)[44], i.e., there is not much variation in the estimates presented in columns (3), (4) and (5). According to these results, the effect of cumulative child care use since child birth ranges between -0.0061 and -0.0074. That means that an additional quarter of child care use is associated with a reduction of about 0.74% in child's test scores. This implies that using child care for one additional year, which reduces maternal contact time with the child, is associated with a reduction of about 3.0% in child's test scores, approximately 0.13 standard deviations.

These results are strikingly similar to child care effects reported by Bernal and Keane

[44] Both use the same set of welfare rules and child care subsidy rules as exclusion restrictions.

(2005). In that paper we estimated the cognitive ability production function (13) by using the same set of welfare rules and child care subisidy rules as instrumental variables. There, our estimates implied that one year of full-time work and day care use would lower a child's test scores by 2.9%. 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 approach implements a selection correction (for the problem that arises because children who are placed in day care and/or having working mothers may differ systematically from children who are not) in a somewhat different way. Thus, it is comforting that results are so robust across the two approaches.

The fact that we get such similar effects regardless of the selection correction mechanism is evidence in favor of the explanatory power of our set of exclusion restrictions. In other words, this implies that these are powerful instruments that predict a good deal of the variation in our endogenous variables which allows us to identify the effects of interest with precision.[45]

The effect of cumulative household income does not turn out to be statistically significant under most of the estimation methods, however, it is positive and significant once we estimate the approximate solution of our structural model. The estimated effect of household income since the birth of the child is quantitatively small. In particular, a 1% increase in cumulative household income is associated with an increase of 0.016% in child's test scores which is equivalent to 0.003 standard deviations. This effect is considerably small especially if we compare it with the estimated child care effect. For example, if cumulative household income were to double, e.g. because the mother decides to work twice as much during the period since the birth of the child, then that extra income would be associated with a 1.6% increase in the child's scores. However, the negative effect of <u>each</u> additional year of child care use (required because the mother worked more) is almost twice as much this amount, i.e, 3.0%. That means, that while income has a positive effect on the child's achievement it does not come close to completely offsetting the effect of maternal separation.

Given that we include controls for maternal education and AFQT, this result is consistent with a view that permanent income is significant in determining parental investment in children,

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[45] The power of this set of instruments is particularly striking if we compare these results with prior studies that have used IV methods to estimate the effect of maternal time inputs on children's achievement. In Section 2 we discussed at length several issues related to the use of weak instruments by James-Burdumy (2005) and Blau and Grossberg (1992).

and hence the children's achievement, while transitory income is less relevant.

One advantage of the quasi-structural approach over the simpler single equation IV approach is that, by explicitly estimating the work and child care decision rules, and by including the mother's wage function as part of the system, we achieve a rather substantial efficiency gain. Indeed, the standard error on the cumulative childcare use coefficient in the log test score equation falls by a factor of 6, giving us much greater confidence in the estimated effect size.[46] This arises in part because the residual in the wage equation conveys information about the mother's unobserved skill endowment, and hence about the unobservable in the test score equation. In addition, note in Table 4 how the standard errors on most of the observable characteristics in column (5) are smaller compared to those estimated by IV in columns (3) and (4). This implies that by imposing some structure we obtain an efficiency gain while getting estimates that are very close to the IV effects.

In Table 5 we present estimates of the initial wage equation and the re-employment wage equation. All parameters show the expected sign and reasonable magnitudes. For example, one additional year of education is associated with 3.9% increase in initial wages. Similarly, an additional quarter of working experience is associated with a 1.4% increase in reemployment wages.

In Tables 6 and 7 we present estimates of the work and child care use probits. The estimates associated with the welfare rules and day care subsidy rules are remarkably reasonable. For example, the length of the time limit in the State of residence of the mother significantly reduces the probability that the mother works (and hence decreases the probability of using day care) and to a greater extent in the case of full-time work as one would expect. Similarly, the length of the work requirement clock significantly reduces the probability that a mother works. The number of work requirement exemptions significantly decreases the probability that a mother works full-time but increases the probability that she works part-time (although the magnitude of this effect is small). As one would expect, both the flat earnings disregard and the percentage disregard increase the probability that a mother works (both full-time and part-time).

The EITC phase-in rate significantly decreases the probability that a mother works full-time but increases the probability that she works part-time. This result is consistent with previous findings by Keane and Moffitt (1998). Using the estimates of a structural model of welfare

[46] Using linear IV, the coefficient is -.00741 with a standard error of .0029 (t = -2.56).

participation, the authors simulate the effect of an EITC-type of policy. Their results indicate that the EITC encourages part-time work more than it does full-time work. By looking at Table 6 one can observe that something similar happens with the effect of the Child Support Enforcement program expenditure per single mother.

The average wage at the 20th percentile of the wage distribution of the State of residence significantly increases the probability of full-time work and reduces the probability of part-time work as one would expect. In addition, the percentage of the population employed in the services sector significantly increases the probability of work.

Some of the estimates are less intuitive. For example, a higher unemployment rate in the State of residence increases the probability of work. However, the magnitude of this effect is pretty small in both cases (full-time and part-time). The effect of the Child Care Development Fund expenditure per single mother is negative on the probability of working and the probability of using child care. However, the effect is statistically insignificant in the case of part-time work. This might imply that the income effect dominates the substitution effect, i.e., the subsidy increases household income and hence induces a reduction in the hours of work rather than encouraging work due to the availability of cheaper daycare.

6.2. Model Fit

Figure 2 depicts the fit of the quasi-structural model to the choice distributions in Figure 1, based on a simulation of 15,000 individuals. As can be observed, the quasi-structural model matches the data quite well, in particular, in the case of the most chosen alternatives, i.e., stay at home and do not use childcare and work full-time and use child care. Chi-squared goodness-of-fit test statistics shown in Table 8 confirm the graphical results. In addition, predicted wages by mother's characteristics and predicted log average scores by child's age (shown in Figure 3) fit the data quite closely as well.

7. Conclusions

This paper evaluates the effects of home inputs on children's cognitive development using the sample of single mothers in the National Longitudinal Survey of Youth (NLSY). In particular, we assess the effects of child care use (which in our framework tends to reduce maternal contact time with the child) and household income on children's test scores at 3, 4, 5 and 6 years old. In order to deal with the selection problem that arises because of 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." We take advantage of the plausibly exogenous variation in employment and child-care choices generated by the differences in welfare regulations across states and over time introduced by the welfare reform legislation of 1996, and prior to that by Section 1115 Welfare Waivers, to help identify the selection model. These welfare rules provide natural exclusion restrictions, as it is plausible that they enter the decision rules for employment and day care use, while not entering the child cognitive ability production function directly. The instruments are quite powerful, in the sense that they explain a substantial part of the variation in work and day care use by single mothers.

The main changes in the welfare system under both Section 1115 Waivers and TANF that are relevant for our exercise could be grouped into the following categories: termination and work requirement time limits, earnings disregard, child care assistance and child support enforcement. States differ greatly in terms of the rules they have adopted in each of these dimensions. Thus, we construct an extensive set of State and individual-specific welfare rules variables, and use these as exclusion restrictions which help us identify the selection model. Most of the leverage for identification comes from comparing behavior and child outcomes of women who had children between 1990 and 2000, so they were impacted by welfare waivers and TANF, with women whose children were born earlier, since these two groups are subject to very different welfare rules.

Our results imply that if a mother works full-time, while placing a child in day care, for one full year, this reduces the child's cognitive ability test score by 3.0%, which is 0.135 standard deviations.[47] The result we obtain here is very similar to what we obtained in Bernal and Keane (2005), where we adopted a single equation instrumental variable (IV) approach. There, our estimates implied that one year of full-time work and day care use would lower a child's test scores by 2.9%. 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 approach implements a selection correction (for

[47] The coefficient on the coefficient capturing the effect of full-time quarterly work and day care use in the log test score equation is -.00747 with a standard error of .00048 (t = -15.56). This implies an effect of -.02988 for a full year. The standard deviation of log scores is .2204.

the problem that arises because children who are placed in day care and/or having working mothers may differ systematically from children who are not) in a somewhat different way. Thus, it is comforting that results are so robust across the two approaches.

The estimated effect of household income since the birth of the child is quantitatively small. In particular, a 1% increase in cumulative household income is associated with an increase of 0.016% in child's test scores which is equivalent to 0.003 standard deviations. This effect is considerably small especially if we compare it with the estimated child care effect. For example, if cumulative household income were to double (e.g., because the mother decides to work twice as much during the period since the birth of the child) then that extra income would be associated with a 1.6% increase in the child's scores. However, the negative effect of each additional year of child care use is almost twice as much this amount, i.e, 3.0%. That means, that while income has a positive effect on the child's achievement it does not come close to completely offsetting the effect of maternal separation. Given that we include controls for maternal education and AFQT, this result is consistent with a view that permanent income is significant in determining parental investment in children, and hence the children's achievement, while transitory income is less relevant.

One advantage of the quasi-structural approach over the simpler single equation IV approach is that, by explicitly estimating the work and child care decision rules, and by including the mother's wage function as part of the system, we achieve a rather substantial efficiency gain. Indeed, the standard error on the cumulative childcare use coefficient in the log test score equation falls by a factor of 6, giving us much greater confidence in the estimated effect size.[48] This arises in part because the residual in the wage equation conveys information about the mother's unobserved skill endowment, and hence about the unobservable in the test score equation. On the other hand, misspecification of the joint distribution of the unobservables across the four equations of the system could lead to inconsistency.

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

[48] Using linear IV, the coefficient is -.00741 with a standard error of .0029 (t = -2.56).

is larger (3%), but the similarity of the results is striking.

Bernal's (2003) paper relied on very different exclusion restrictions from those used here. She treats the age profiles of husband and wife earnings as exogenous, in the sense that (1) only the parents skill endowments, and not their age, affects the skill endowment that the child inherits, and (2) only skill endowments and permanent income of mothers and husbands, and not short run fluctuations in household income (such as those generated by movement along the age path) affect the endowments they transmit to children, or their investment in children. Otherwise identical women who have children when they or their husbands are at different parts of the life-cycle age path will have different incentives to work. This creates exogenous variation in work incentives (uncorrelated with child ability endowments) that help to identify effects of maternal time inputs. While we find this approach to identification appealing, we think the welfare policy rules we use here are more appealing, as their exogeneity is less subject to challenge.

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

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Table 1

List of Instruments

Variable	Description
	Individual Level Welfare Policy Variables
BEN_{ist}	Real AFDC/TANF maximum benefits, calculated using the state level benefit rule and the mother's family composition.
$EITC_{ist}$	EITC phase in rate constructed from both the federal and state level
TL_HIT_{ist}	Dummy variable indicating whether a woman would have hit time limit
$ELAPSED\_TL\_HIT_{ist}$	Time elapsed since woman *i* may potentially be subject to time limit
$REMAIN\_TL\_ELIG_{ist}$	Maximum potential remaining length of a woman's time limit, constructed: $TL\_LENGTH_{st}-\min\{AGE\_OLDEST\_CHILD_{ist}, ELAPSED\_TL_{st}\}$
$REMAIN\_ELIG_{ist}$	Remaining length of time to be categorically eligible for welfare benefits: $18-AGE\_YOUNGEST\_CHILD_{ist}$
WR_HIT_{ist}	Indicator for whether a woman could be subject to a work requirement: =1 if$[WR_LENGTH_{st}\leq\min\{AGE_OLDEST_CHILD_{ist}, ELAPSED_WR_{st}\}$ & $AGE\_YOUNGEST\_CHILD_{ist}\geq AGE\_CHILD\_EXEM_{st}]$
$ELAPSED\_WR\_HIT_{ist}$	Time elapsed since woman *i* may be potentially subject to work requirement
	State Level Policy Variables
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*.
$ELAPSED\_TL_{st}$	Time (in months) elapsed since the implementation of time limit in state *s*.
$DCHILDBEN_{st}$	Dummy variable indicating whether the child portion of the welfare benefit continues after time limit exhaustion
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*.
$ELAPSED\_WR_{st}$	Time (in months) elapsed since the implementation of work requirement in state *s*.
$CHILD\_EXEM_{st}$	Dummy for whether state *s* has age of youngest child exemption in place at *t*
$AGE\_CHILD\_EXEM_{st}$	Age of youngest child below which the mother will be exempted from work requirement in state *s* at time *t*.
$WR\_ULT\_SANC_{st}$	Dummy for whether state *s* has a full sanction for non-compliance of work requirement in state s at time t.
$EXEMP_{st}$	Number of work requirement exemptions in state *s*
$FLAT\_DISREGARD_{st}$	Flat amount of earnings disregarded in calculating the benefit amount.
$PERC\_DISREGARD_{st}$	Benefit reduction rate (Does not include phase-out)
$CHILDCARE_{st}$	CCDF expenditure per single mother in state *s* at time *t*.
$ENFORCE_{st}$	Child support enforcement expenditure in state *s* at year *t* per single mother.
	Other Local Market Variables
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*.

Table 2

Mean Characteristics of Mothers in the Sample

Description		NLSY	Sample	ttest
Worked within 4 quarters after birth		0.47	0.39	**
		(0.004)	(0.015)	
Mother's age in years at birth		24.8	23.13	**
		(0.053)	(0.054)	
Mother's education in years at birth year		12.0	11.2	**
		(0.024)	(0.054)	
Hispanic or Black		0.47	0.83	**
		(0.004)	(0.013)	
Hourly wage before birth		6.71	4.39	**
		(0.22)	(0.06)	
	Obs	5728	977	
Total number of children of mother		2.83	3.12	**
		(0.012)	(0.043)	
Father present at birth		0.55	-	
		(0.004)		
Observations		4,814	1,464	

Table 3

Summary of Variables used in the Empirical Analysis

Variable	Mean (standard error)
log(Test Score)	4.49855
	(0.2204)
Mother's education	11.208
	(1.8972)
Mother's age	23.136
	(4.5820)
Boys (Children of single mothers)	0.4976
	(0.5001)
Hispanic or Black	0.8262
	(0.3790)
Birthweight	111.97
	(21.9760)
Mother worked before giving birth	0.6431
	(0.4792)
Wage rate prior to giving birth	4.3938
	(2.0075)
Accumulated work experience prior	4.7202
to giving birth (number of years)	(6.0088)
Average Yearly Income (Thousands)	10.92743
	(13.5677)
Cumulative Income (Thousands)	51.1787
	(67.4148)
Average Child Care Use (% of periods)	0.3777
	(0.3203)
Cumulative Child Care Use (Quarters)	7.0923
	(6.1273)

Table 4

Test Score Equation

	(1) OLS	(2) RE	(3) I.V.	(4) I.V.	(5) Max. L.
Cumulative Child Care	0.0006	0.000173	-0.00741	-0.00614	-0.00747
	(0.00066)	(0.00083)	(0.0029) **	(0.0023) **	(0.00048) **
Log(Cumulative Income)	-0.00267	-0.00410	0.01772	-0.02981	0.016838
	(0.00453)	(0.00569)	(0.0207)	(0.0140) *	(0.00477) **
Gender	-0.02361	-0.02298	-0.02585	-0.02651	-0.020607
	(0.00572) **	(0.00740) **	(0.00589) **	(0.00590) **	(0.00384) **
Birthweight	0.00433	0.00436	0.00464	0.006298	0.0107694
	(0.00459)	(0.00595)	(0.00479)	(0.00476)	(0.00280) **
Mother's education	0.01057	0.01121	0.01283	0.01501	0.01336
	(0.00201) **	(0.00259) **	(0.0025) **	(0.0024) **	(0.00133) **
Mother's AFQT	0.00140	0.00139	0.00136	0.00165	0.00155
	(0.00020) **	(0.00025) **	(0.0002) **	(0.0002) **	(0.00054) **
I[AFQT missing]	0.05533	0.06444	0.05857	0.05848	0.0321918
	(0.01796) **	(0.02305) **	(0.01858) **	(0.01855)	(0.01575) **
I[age>20]	0.02237	0.02306	0.02050	0.030543	0.050868
	(0.00803) **	(0.01023) **	(0.01032) **	(0.00904) **	(0.00579) **
I[age>=33]	0.00713	0.00874	0.00183	0.01354	0.0018583
	(0.01697)	(0.02167)	(0.02139)	(0.02101)	(0.01396)
Race	-0.05047	-0.05523	-0.03906	-0.04516	-0.039127
	(0.00871) **	(0.01110) **	(0.01070) **	(0.00987) **	(0.00571) **
Number of siblings	-0.01775	-0.01806	-0.02167	-0.02477	-0.014464
	(0.00244) **	(0.00314) **	(0.00281)	(0.00479) **	(0.00983)
Experience before	0.00077	0.00091	0.00657	0.011014	0.002860
	(0.00065)	(0.00085)	(0.00537)	(0.00501) **	(0.06442)
I[worked before]	0.01112	0.01345	0.03030	0.031458	0.0264632
	(0.00742)	(0.00955)	(0.01118) **	(0.01025) **	(0.00474) **
Child's age	0.02969	0.03269	0.03959	0.052609	0.037828
	(0.00657) **	(0.00615) **	(0.00997) **	(0.00878) **	(0.01687) **
PPVT dummy	-0.25197	-0.25045	-0.25284	-0.25154	-0.246814
	(0.00908) **	(0.00949) **	(0.00928) **	(0.00930) **	(0.00865) **
MATH dummy	-0.07741	-0.07715	-0.07789	-0.07762	-0.07225
	(0.00699) **	(0.00588) **	(0.00713) **	(0.00715) **	(0.01016) **
Constant	4.46790	4.46383	4.36375	4.477315	4.4618675
	(0.03264) **	(0.03977) **	(0.07248) **	(0.06255) **	(0.00378) **
R^2	0.374	0.374	0.351	0.347	
MSE_{ML}	0.03020	0.03322	0.03155	0.03174	0.03130
Fraction due to permanent	-	0.334788	-	-	0.2414316

(1) Assumes welfare rules have same effect in all years
(2) Assumes welfare rules have year-specific effects
(5) Full quasi-structural model

Table 5

Initial Wage Equation

	Variable	Parameter	Std. Error
β_{80}	Intercept	0.312691	(0.013614)
β_{83}	age	0.015965	(0.000348)
β_{85}	education	0.039180	(0.001004)
β_{86}	race	0.189202	(0.006306)
β_{861}	AFQT	0.004126	(0.000109)

Re-employment Wage Equation

	Variable	Parameter	Std. Error
β_{66}	t	-0.001714	(0.008075)
β_{67}	E_t	0.013903	(0.002491)
β_{68}	f_{t-1}	0.100997	(0.021118)
β_{69}	p_{t-1}	0.072053	(0.059163)
β_{70}	E_tXeduc	0.003488	(0.019730)

Table 6

Full-Time Probit

	Variable	Parameter	Std. error
β_{01}	Intercept	-18.195746	(0.033332)
β_1	age	0.233865	(0.001746)
β_2	age^2	-0.006366	(0.000041)
β_3	education	0.307556	(0.001363)
β_4	race	0.437699	(0.005602)
β_5	f_{t-1}	1.945201	(0.014412)
β_6	p_{t-1}	1.900432	(0.012920)
β_7	SEP_t	-0.143748	(0.001025)
β_8	AFQT	0.323673	(0.000577)
β_9	D_t	0.044688	(0.000623)
β_{10}	t	0.090635	(0.000336)
β_{11}	BW	-0.114281	(0.003380)
β_{12}	gender	-0.612973	(0.003180)
β_{13}	I[age<20]	0.000443	(0.005242)
β_{15}	$I[C_t>0]$	0.253547	(0.030581)
β_{16}	I[t=1]	-0.614401	(0.029690)
β_{17}	I[t<5]	0.752828	(0.013246)
β_{181}	BEN	0.000055	(0.000019)
β_{183}	TL_LENGTH	-0.179804	(0.004805)
β_{186}	REMAIN_TL_ELIG	0.355393	(0.006183)
β_{188}	REMAIN_ELIG	0.001309	(0.000074)
β_{1811}	WR_LENGTH	-0.017195	(0.005296)
β_{1813}	AGE_EXEM	0.001409	(0.000685)
β_{1814}	EXEMP	-0.824321	(0.035842)
β_{1818}	FLAT_DIS	0.061287	(0.000368)
β_{1819}	PERC_DIS	0.124075	(0.002591)
β_{1821}	ENFORCE	-0.105385	(0.002961)
β_{1822}	EITC	-0.086934	(0.006692)
β_{19}	CHILDCARE	-0.161997	(0.003260)
β_{89}	UE	0.003657	(0.000074)
β_{90}	SWAGE20	0.277932	(0.003570)
β_{91}	SERV	2.138754	(0.026997)
β_{101}	EXPBEF	0.003887	(0.000556)
β_{98}	C_{t-1}	-0.839948	(0.025382)
β_{104}	lnwo	0.087372	(0.004314)

Part-time Probit

	Variable	Parameter	Std. error
β_{02}	Intercept	-10.058533	(0.130153)
$\beta_1/2$	age	-	
$\beta_2/2$	age^2	-	
β_{20}	education	0.331677	(0.005314)
β_{21}	race	0.219302	(0.022283)
$\beta_5/2$	f_{t-1}	-	
$\beta_6/2$	p_{t-1}	-	
β_{22}	SEP_t	-0.069780	(0.004299)
β_{23}	AFQT	-0.080222	(0.001326)
β_{24}	D_t	-0.039899	(0.002691)
β_{88}	t	0.074429	(0.001671)
β_{25}	BW	0.519070	(0.017599)
β_{26}	gender	0.234017	(0.017989)
β_{27}	I[age<20]	0.748807	(0.027282)
β_{29}	$I[C_t>0]$	0.891179	(0.111324)
β_{30}	I[t=1]	-0.013134	(0.001586)
β_{31}	I[t<5]	0.890792	(0.051327)
β_{321}	BEN	0.003414	(0.000117)
β_{323}	TL_LENGTH	-0.058435	(0.007055)
β_{326}	REMAIN_TL_ELIG	0.186911	(0.008927)
β_{328}	REMAIN_ELIG	-0.019805	(0.000448)
β_{3211}	WR_LENGTH	-0.355964	(0.007277)
β_{3213}	AGE_EXEM	0.017580	(0.001579)
β_{3214}	EXEMP	0.032754	(0.050400)
β_{3218}	FLAT_DIS	0.174103	(0.000705)
β_{3219}	PERC_DIS	0.390154	(0.008554)
β_{3221}	ENFORCE	0.646893	(0.022342)
β_{3222}	EITC	0.202820	(0.026396)
β_{33}	CHILDCARE	-0.006182	(0.016339)
β_{92}	UE	0.002546	(0.000336)
β_{93}	SWAGE20	-0.739145	(0.019418)
β_{94}	SERV	1.086172	(0.149179)
β_{99}	EXPBEF	-2.975127	(0.089805)
β_{102}	C_{t-1}	0.154812	(0.002066)
β_{105}	lnwo	0.532798	(0.018908)

Table 7

Childcare Probit

	Variable	Parameter	Std. error
β_{341}	Intercept	-2.331492	(0.211554)
β_{35}	age	0.343983	(0.014531)
β_{36}	age^2	-0.007639	(0.000301)
β_{37}	education	0.046351	(0.002968)
β_{38}	race	0.042904	(0.012192)
β_{39}	f_{t-1}	0.117121	(0.038200)
β_{40}	p_{t-1}	-0.440333	(0.030912)
β_{41}	SEP_t	0.024809	(0.003014)
β_{42}	AFQT	0.004281	(0.000285)
β_{43}	D_t	-0.010794	(0.001176)
β_{44}	t	0.001228	(0.000326)
β_{45}	BW	0.048428	(0.006033)
β_{46}	gender	-0.022052	(0.007933)
β_{47}	I[age<20]	0.331243	(0.015560)
β_{49}	$I[C_t>0]$	0.276229	(0.013245)
β_{50}	I[t=1]	-0.081126	(0.058563)
β_{51}	I[t<5]	-0.116459	(0.034451)
β_{521}	Potential welf. benefits	-0.000735	(0.000036)
β_{523}	TL_LENGTH	-0.023857	(0.011173)
β_{526}	REMAIN_TL_ELIG	0.021019	(0.012473)
β_{528}	REMAIN_ELIG	-0.009598	(0.000536)
β_{5211}	WR_LENGTH	0.021615	(0.004180)
β_{5213}	AGE_EXEM	-0.004172	(0.001788)
β_{5214}	EXEMP	0.151679	(0.036031)
β_{5218}	FLAT_DIS	-0.001464	(0.000268)
β_{5219}	PERC_DIS	-0.012133	(0.005306)
β_{5221}	ENFORCE	0.049152	(0.009008)
β_{5222}	EITC	0.178243	(0.020086)
β_{53}	CHILDCARE	-0.076386	(0.012720)
β_{95}	UE	-0.002137	(0.000139)
β_{96}	SWAGE20	-0.046801	(0.007950)
β_{97}	SERV	-0.258360	(0.062062)
β_{100}	EXPBEF	2.333270	(0.034161)
β_{103}	C_{t-1}	0.028503	(0.001305)
β_{106}	lnwo	0.154787	(0.007777)

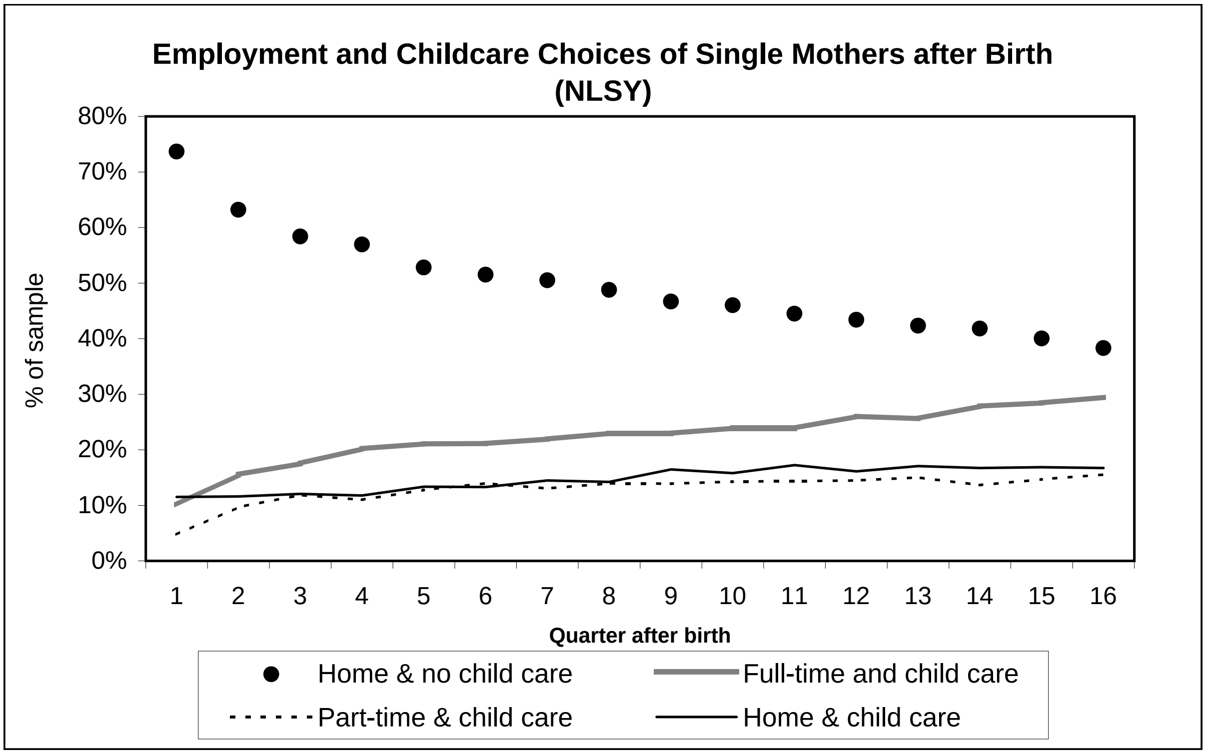
Table 8

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	0.69	0.60	0.90	3.16	5.35	
2	0.00	0.00	0.24	0.17	0.41	
3	1.34	0.08	1.32	1.12	3.87	
4	0.49	1.61	0.50	0.36	2.97	
5	2.34	1.14	0.16	5.94	9.57	*
6	0.92	0.12	2.68	7.80	11.53	*
7	1.17	0.04	0.01	3.24	4.47	
8	0.60	0.02	0.50	4.86	5.99	
9	0.04	0.10	0.03	0.01	0.18	
10	0.08	0.00	0.00	0.17	0.25	
11	0.01	0.92	0.44	0.59	1.97	
12	0.13	0.07	0.73	0.00	0.93	

* Statistically significant at 0.05 (Critical Value=7.82)

Figure 1



Employment and Childcare Choices of Single Mothers after Birth (NLSY)
80%
70%
60%
50%
40%
30%
20%
10%
0%
% of sample
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
Quarter after birth
Home & no child care
Full-time and child care
Part-time & child care
Home & child care

Figure 2

Model Fit to Choice Distributions

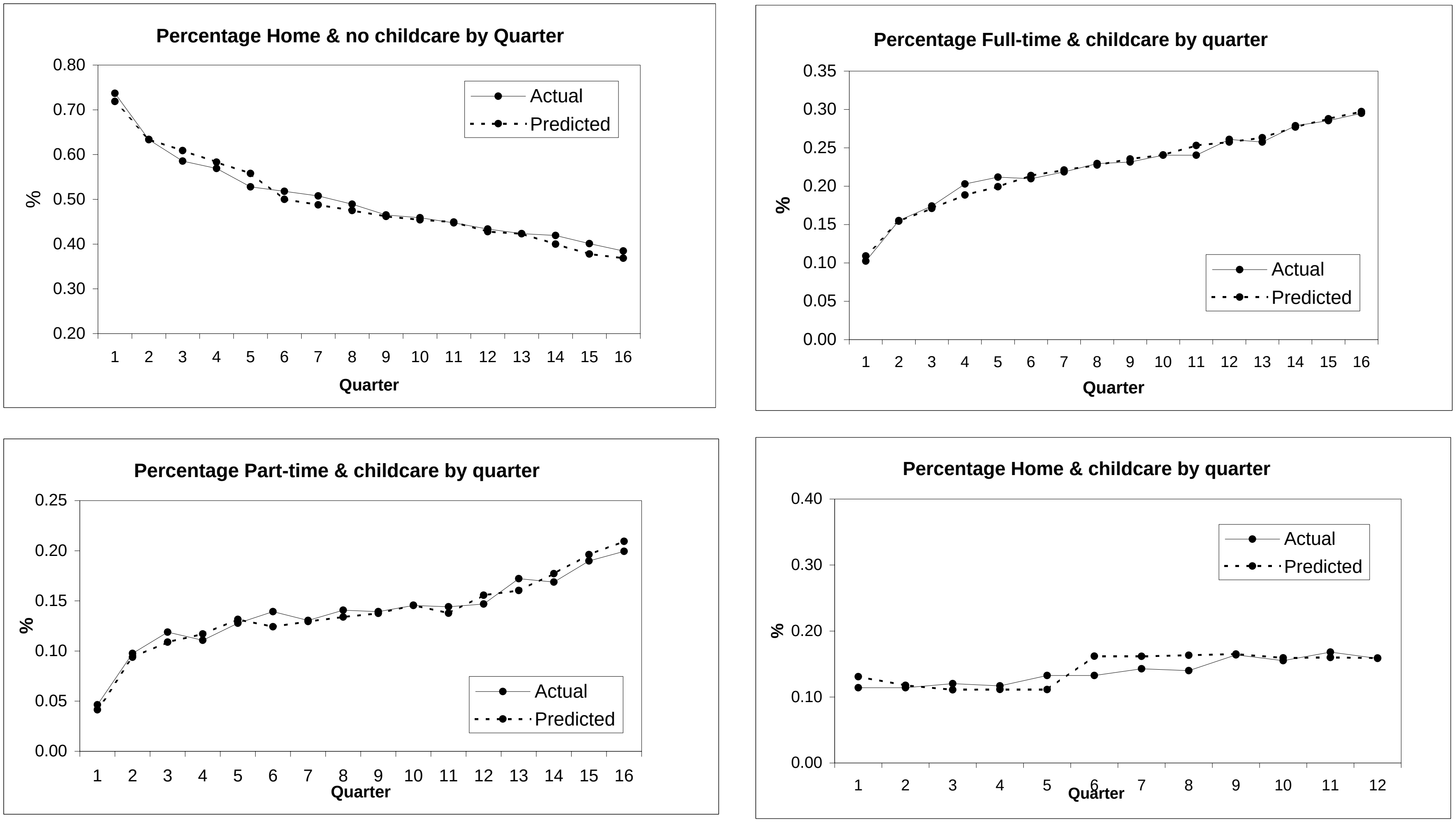
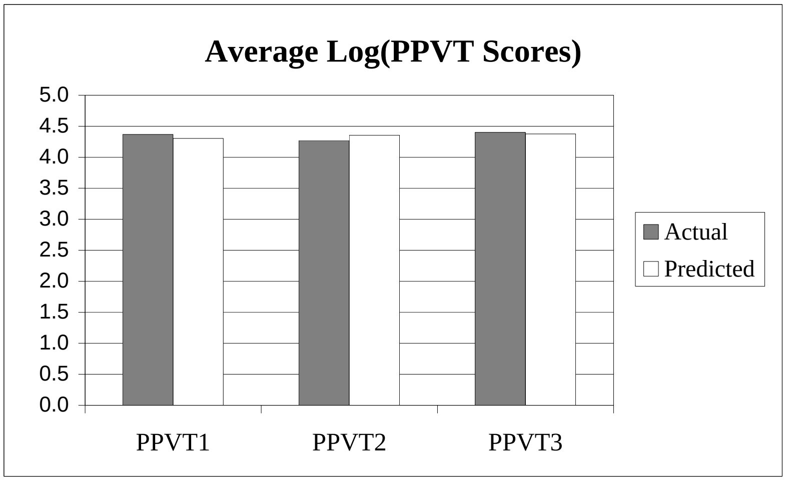
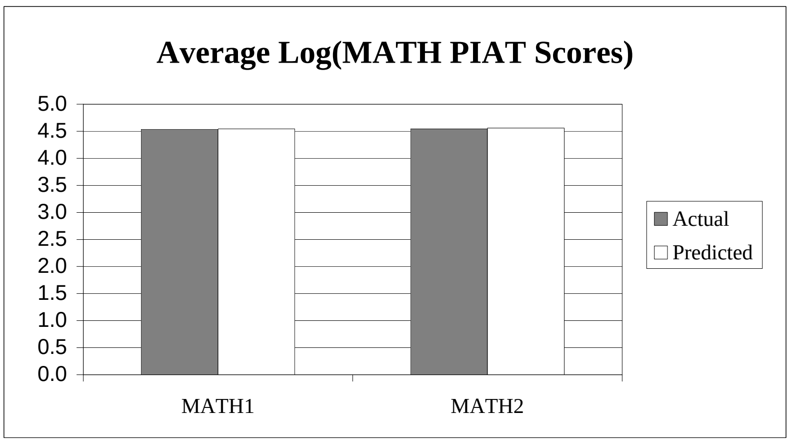
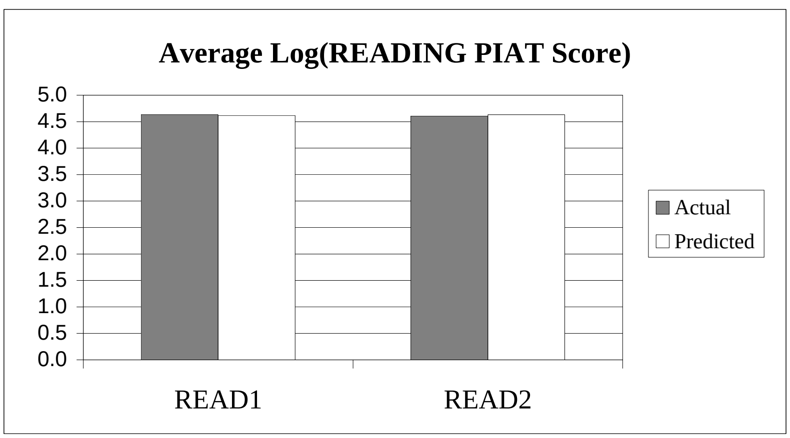


Figure 3


Average Log(PPVT Scores)
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
PPVT1
PPVT2
PPVT3
Actual
Predicted


Average Log(MATH PIAT Scores)
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
MATH1
MATH2
Actual
Predicted


Average Log(READING PIAT Score)
5.0
4.5
4.0
3.5
3.0
2.5
2.0
1.5
1.0
0.5
0.0
READ1
READ2
Actual
Predicted

Appendix 1

Probit we use to predicted 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	0.59202	
	(0.2078)	**
(Whether worked before) x (Avg. wage before)	-0.06419	
	(0.0398)	*
Total work experience (prior to giving birth)	-0.00599	
	(0.0194)	
Child's race	-0.08744	
	(0.1702)	
Child's gender	0.04967	
	(0.1196)	
Mother's education	0.08213	
	(0.0384)	**
Total work experience since child birth	-0.39835	
	(0.0698)	**
Total child care use since child birth	0.22263	
	(0.0527)	**
Whether used child care or not in *t-1*	1.78009	
	(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.

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=1,519)	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

	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