Contents lists available at ScienceDirect

Journal of Econometrics

journal homepage: www.elsevier.com/locate/jeconom

Quasi-structural estimation of a model of childcare choices and child cognitive ability production

Raquel Bernal^a, Michael P. Keane^{b,c,*}

^a Department of Economics and CEDE, Universidad de los Andes, Bogotá, Colombia

^b University of Technology Sydney, Australia

^c Arizona State University, United States

ARTICLE INFO

Article history: Available online 16 September 2009

JEL classification:
C51
J13
J24
Keywords:
Child cognitive development
Childcare
Human capital
Female labor supply

1. Introduction

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

Extensive research shows that early cognitive achievement is a strong predictor of later life outcomes—e.g., high early achievers tend to have higher educational attainment and higher earnings; and are less likely to have teenage births, be on welfare or participate in crime. Bernal and Keane (2008) show, using the National

E-mail address: michael.keane@uts.edu.au (M.P. Keane).

ABSTRACT

This article evaluates the effects of maternal vs. alternative care providers' time inputs on children's cognitive development using the sample of single mothers in the National Longitudinal Survey of Youth. To deal with the selection problem created by unobserved heterogeneity of mothers and children, we develop a model of mother's employment and childcare decisions. We then obtain approximate decision rules for employment and childcare use, and estimate these jointly with the child's cognitive ability production function. To help identify our selection model, we take advantage of the plausibly exogenous variation in employment and childcare choices of single mothers generated by the variation in welfare rules across states and over time created by the 1996 welfare reform legislation and earlier State waivers.

© 2009 Elsevier B.V. All rights reserved.

Longitudinal Survey of Youth (NLSY), that the test scores as early as ages 4–6 are strongly correlated with the completed education for children of single mothers.¹ Thus, understanding the determinants of early cognitive achievement may be critical for the design of public policy aimed at improving subsequent labor market outcomes (see Cunha et al. (2006)). However, the question of what determines child cognitive achievement in general, and the role of parental time and goods inputs in particular, remains largely unresolved.

Two key problems hamper research in this area: (1) a paucity of good data on inputs into child cognitive development, and (2) the difficult selection problem arising because inputs into child development may be correlated with unobserved characteristics of parents and children. In this article, we tackle a small aspect of this general problem, by looking at the effects of maternal vs. alternative care provider time inputs, and household income, on child cognitive ability test scores recorded at ages 4–6. For this purpose, we use data on single mothers from the 1979 NLSY. It is useful to focus only on single mothers for reasons we describe below.

In studying the effects of maternal time inputs on child outcomes, two sources of selection bias are of key concern: (1) women



^{*} Corresponding address: PO Box 123, Broadway, NSW 2007, Australia. Tel.: +61 2 9514 9742; fax: +61 2 9514 9743.

^{0304-4076/\$ -} see front matter © 2009 Elsevier B.V. All rights reserved. doi:10.1016/j.jeconom.2009.09.015

¹ They find, for example, that a 1% increase in the PIAT math test score at age 6, holding parental background variables like mother's education and IQ fixed, is associated with an increase in educational attainment (measured at age 18 or later) of approximately .019 years. For reading scores the figure is 0.025 years.

that work/use childcare may differ systematically from those that do not; (2) child cognitive ability may itself influence a mother's decisions about work/childcare. To illustrate problem (1), suppose that high-skilled women are more likely to have high cognitive ability children, and more likely to work/use childcare. Then, a statistical analysis may find a spurious positive effect of maternal employment/childcare use on cognitive outcomes. To illustrate (2), suppose mothers of low ability endowment children compensate by spending more time with them, and thus tend to work less. Again, the estimated effect of maternal employment/childcare on child cognitive outcomes is upwardly biased. Clearly, these selection issues make evaluating effects of women's decisions on child outcomes very difficult.

The data on single mothers in the NLSY79 provide an important opportunity to address these selection problems. A subset of these women was affected by the 1996 reform of the US welfare system that created the Temporary Aid to Needy Families (TANF) program, or by earlier State welfare waivers, and/or by substantial increases in childcare subsidy spending by the ChildCare Development Fund (CCDF). These rule changes had strong effects on the incentives for single mothers to work and use childcare. In fact, the percentage of single mothers who work increased from 67% in 1992 to 79% in 2001, with even larger 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/use childcare prior to our observations on their children's test scores. Women whose children reached ages 4–6 prior to the start of the reforms were not affected by these changes. This source of variation helps identify the effect of maternal work/childcare use on child outcomes.³

This discussion gives an intuition for our approach, but it may seem to suggest a simple before-and-after welfare reform comparison of test score outcomes and levels of maternal work—as in the natural experiment/instrumental variable (IV) literature. But this over-simplifies the approach we actually take. As Rosenzweig and Wolpin (2000) stress, what IV estimates depends on what one controls for. For example, welfare reform may have altered goods inputs, not just time inputs. Thus, to interpret our estimates, we must (i) adopt a particular theoretical model, including a specification of a child cognitive ability production function, and (ii) consider how this relates to the outcome equation we actually estimate (i.e., not all production function inputs are observed due to data limitations, complicating interpretation. We discuss this in Section 4.1).

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

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

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

Another advantage is that, by estimating the work and childcare decision rules, the wage function and the production function as a system, we achieve a rather substantial efficiency gain. Indeed, the standard error on the cumulative childcare use coefficient in the log test score equation falls by a factor of 7.4, giving us much greater confidence in the estimated effect size.⁴ This occurs in part, because the wage equation residual conveys information about the mother's unobserved skill endowment, and, hence, about the unobservable in the test score equation.

On the other hand, a disadvantage of the quasi-structural approach is that mis-specification of the joint distribution of the unobservables in the four-equation system may lead to inconsistency.⁵ Another advantage of single equation IV is its relative simplicity of implementation which, in Bernal and Keane (2008), enables us to examine a large number of alternative specifications of the child cognitive ability production function.⁶ Given the time required to estimate the quasi-structural system, such extensive testing is not practical here.

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

This has both advantages and disadvantages. While it may provide more robust estimates, the failure to fully specify the model creates problems when it comes to policy simulation. For instance, a change in welfare policy may have very different effects on maternal work/childcare use, and goods inputs, depending on whether it is perceived as permanent or transitory.⁷ Thus, to simulate effects of policy changes on maternal decisions and child out-

 $^{^2}$ From 57% to 78% for never married single mothers, 40% to 61% for those with low education, 59% to 78% for those with children aged 0–5, 34% to 67% for those with 3 + children, and 57% to 76% for African-Americans.

³ Our description suggests that there was a point in time when welfare rules simply became stricter. But, this is an over-simplification to facilitate exposition. A key aspect of the 1996 welfare reform, and of earlier welfare waivers, was to give States greater flexibility in setting rules. Thus, there was a great deal of heterogeneity across the US States in the timing and nature of welfare rule changes. See, e.g., Fang and Keane (2004) for an extensive discussion.

⁴ Using linear IV, the coefficient on quarters of childcare is -0.00807 with a standard error of 0.00333 (t = -2.42). For a version of the quasi-structural model with homogeneous childcare effects, the coefficient is -0.00698 with a standard error of 0.00045 (t = 15.5).

⁵ Another approach that might be less sensitive to this problem is to estimate the four-equation system by method of moments (MOM). Of course, MOM has its own problems, such as loss of efficiency relative to ML estimation of the system, and potential sensitivity of results to choices of instruments and weighting matrices.

⁶ For example, it may be cumulative inputs that matter, analogous to the Mincer earnings specification where cumulative schooling and work experience affect current human capital, or it may be average inputs, or more recent inputs, that matter more. Or, different types of childcare, such as formal vs. informal, may differentially affect child outcomes.

⁷ See Keane and Wolpin (2002a,b) for a detailed discussion of these issues.

comes, we cannot avoid making assumptions (either explicitly or implicitly) about expectations.⁸

Our study of single mothers extends earlier work by Bernal (2008) on children of married women in the NLSY. Using a fully structural approach, she found that one year of maternal full-time work and childcare results in an 1.8% reduction in child cognitive ability test scores. A key motivation of our work was to see if that result generalizes from married to single mothers. Our estimate for single mothers is larger (2.7%), but the similarity of the results is still striking.

Bernal (2008) relied on very different exclusion restrictions from those used here. She treats age profiles of husband and wife earnings as exogenous, in that: (1) only parents' skill endowments, and not their age, affect the skill the child inherits, and (2) only skill endowments and permanent income of mothers and husbands, and not short run fluctuations in household income (e.g., due to movement along the wage/age path) affect investment in children. Thus, otherwise identical women who have children when they or their husbands are at different points in the life-cycle will have different incentives to work. This creates exogenous variation in work/childcare use that helps identify the effects of maternal time inputs.⁹ We find this approach appealing, but exogeneity of the welfare policy rules used here seems less subject to challenge.

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

2. Literature review

Many prior studies, mostly in developmental psychology, use the NLSY to assess effects of maternal employment or childcare on child cognitive development. For reviews see Haveman and Wolfe (1994), Lamb (1996), Love et al. (1996), Blau (1999), Ruhm (2002) and Bernal and Keane (2008). Most studies present simple correlations of inputs and child outcomes, not controlling for family or child characteristics. Rarely are controls for selection bias implemented.¹⁰

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

The diversity of these results may stem from the wide range of specifications that are estimated, and the common limitation of failing to control for selection bias. To make our exposition of the literature more clear, it is useful to have a specific framework in mind.¹¹ Consider the following equation, interpretable as a cognitive ability production function:

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

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

While (1) is the general setup that, at least implicitly, underlies most articles in the literature, none actually estimate this equation and many depart from it greatly. One fundamental problem is that the maternal time input *T* and goods inputs *G* are not directly observed. Most articles ignore this problem, simply using maternal employment or childcare use in place of maternal time. And most use only one of these variables, rather than examining both.¹² Similarly, most articles simply ignore G.¹³ A few proxy for it using household income or the NLSY's "HOME" environment index. The latter is problematic as it is based not just on goods inputs but also maternal time inputs. To our knowledge, only James-Burdumy (2005) discusses the relationship between her estimating equation and a child ability production function, by noting the difficulty in interpreting estimates when proxies are used for maternal time and goods inputs.

Second, most articles include only current inputs. This is a strong assumption, especially as the human capital literature has emphasized cumulative inputs. Of course, in a more general specification the whole history of inputs since birth may matter for time t outcomes. Few articles discuss their assumptions regarding timing of inputs.¹⁴ We discuss these issues in Section 4.

Finally, most articles estimate Eq. (1) by OLS, ignoring potential endogeneity of the inputs—i.e., correlation of maternal work and childcare use decisions, and goods inputs, with the unobserved ability endowments, μ_j and δ_{ij} . A few recent studies try to overcome this problem by using either: (1) an extensive set of explanatory variables to proxy for unmeasured endowments, (2) child or

⁸ More subtly, the perceived persistence of welfare policy changes may influence what IV and quasi-structural estimates of maternal time effects mean. For example, a permanent rule change that leads to a permanent increase in work effort might induce mothers to increase goods inputs into children to compensate, or to increase "quality" time as a share of total time, etc.. A transitory rule change might not have such effects. Thus, the estimated effect of maternal time inputs may differ depending on the perceived persistence of the rule change that induced them.

⁹ In the NLSY data Bernal (2008) 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).

¹⁰ See for example, Burchinal et al. (1995) and Parcel and Menaghan (1990).

¹¹ Todd and Wolpin (2003, 2005), Rosenzweig and Wolpin (1994) and Rosenzweig and Schultz (1983) also discuss estimation/specification of cognitive ability production functions, and raise many of the issues raised here. We focus on specific issues that arise in estimating effects of parental time, childcare and goods inputs on child development.

¹² For example, Vandell and Ramanan (1992) estimate the effect of maternal employment on child cognitive outcomes but do not include childcare arrangements as an additional input. Similarly, Caughy et al. (1994) assess the effect of childcare participation but do not include maternal time inputs in their specification.

¹³ For example, Baydar and Brooks-Gunn (1991) estimate the effects of both maternal employment and childcare arrangements but do not include goods/services (or a proxy such as household income) in the production function.

¹⁴ Notable exceptions are Blau (1999) and Duncan and NICHD Early ChildCare Research Network (2003). Some articles use maternal employment (and/or childcare use) at different years after childbirth, but do not discuss implications in terms of the underlying production function (e.g., Waldfogel et al. (2002), Vandell and Ramanan (1992), Baydar and Brooks-Gunn (1991)).

family fixed effects (FE), or "value-added" models, and/or (3) instrumental variables.

Consider first studies that use extensive controls, such as Baydar and Brooks-Gunn (1991), Vandell and Ramanan (1992), Parcel and Menaghan (1994), Han et al. (2001) and Ruhm (2002). They control for many observed characteristics of the mother and child, including the mother's AFQT score—a measure of IQ available in the NLSY. But they still obtain inconclusive results. For example, Baydar and Brooks-Gunn (1991) find maternal work during the child's first year negatively affects cognitive outcomes, while Vandell and Ramanan (1992) report positive effects of early employment on math scores, and of current employment on reading scores. Ruhm (2002) finds significant negative effects of maternal employment on math scores, while Parcel and Menaghan (1994) find small positive effects of employment on cognitive outcomes.

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

James-Burdumy (2005) estimated household FE models on 498 siblings from the NLSY. She finds the effect of maternal employment varies by the cognitive assessment used and the timing of employment.¹⁵ By taking sibling differences, one eliminates the mother fixed effects μ_j from (1), but not the child fixed effects δ_{ij} . If mothers make time compensations for children depending on their ability type, a household fixed effect model is not appropriate, as maternal employment is correlated with the child specific part of the cognitive ability endowment. The FE estimator also requires that input choices are unresponsive to prior sibling outcomes. If inputs to child *i'* are responsive to outcomes for child *i*, then ε_{ijt} will be correlated with those inputs.

Blau (1999) and Duncan and NICHD Early ChildCare Research Network (2003) study effects of childcare use and childcare quality on child outcomes. They use similar methodologies, including a wide range of proxies for the child ability endowment (like mother's AFQT and education), controls for many aspects of the home environment, and use of FE and value-added specifications.¹⁶ The main difference is that Blau uses the NLSY, while Duncan uses the NICHD Study of Early ChildCare. Blau (1999) concludes "childcare inputs ...during the first three years of life have little impact on ...child outcomes ..." while Duncan finds a modest positive effect of improved childcare quality.¹⁷

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

¹⁵ According to the FE estimates in her Table 5, an increase in maternal work from 0 to 2000 hours in year 1 of a child's life reduces the PIAT math score (measured at ages 3–5) by (-0.00117) $\times 2000 = -2.34$ points. This is similar to the effect we estimate for one year of full-time work (-2.7%). But she finds no significant effect of maternal work after the first year, so her estimate of the effect of five years of full-time employment is much smaller than ours.

effects of those variables holding the HOME index fixed. In contrast, we are interested in the total impact of the maternal time input on child outcomes—including how a decline in the time input (due to increased work/childcare use) affects time spent reading to the child and so on.

Blau (1999) and Duncan and NICHD Early ChildCare Research Network (2003) also contain useful discussions of the limitations of FE and value-added specifications. As they point out, neither provides a panacea for dealing with unobserved child ability, as both rely on assumptions that are, in some ways, stronger than OLS. For example, the household FE estimator requires that input choices be unresponsive to the child-specific ability endowment. The valueadded model runs into the problem that the estimates of lagged dependent variable models are inconsistent in the presence of fixed effects.¹⁸ Neither approach, nor child fixed effects, deals with the endogeneity problem that arises because current inputs may respond to lagged test scores. One way to approach this problem is linear IV.

Only two articles have attempted to use IV—Blau and Grossberg (1992) and James-Burdumy (2005). Both look at the effects of maternal work on child outcomes, and do not examine childcare effects per se. More importantly, both articles use extremely weak instruments. As a result, the standard errors on the maternal work variables in their 2SLS regression are so large that no plausibly sized effect could possibly be significant (i.e., in each case, to attain 5% significance, maternal work over a three year period would have to change a child's tests scores by roughly 50 points or 3 standard deviations).¹⁹ Thus, we would argue that their attempts to implement IV were not successful.

In contrast, the welfare policy and local demand instruments we employ are much stronger. Indeed, in Bernal and Keane (2008), where we implement an IV approach, we note that first stage marginal R^2 values obtained using these instruments (i.e., about 0.09) are fairly large relative to what one typically sees in the IV literature, and, in the second stage, standard errors on maternal work and childcare use do not "explode" when these instruments are used.

Finally, Bernal (2008) estimates a structural model of work and childcare decisions of married women after childbirth. Estimating the cognitive ability production function jointly with mothers' decision rules adjusts for the selection arising because certain types of children are more likely to be in childcare and/or have working mothers. Her results suggest an additional year of full-time work and childcare reduces test scores by about 1.8% (at ages 3–7).

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

¹⁶ 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.

¹⁷ In particular, a one standard deviation increase in childcare quality causes a 0.04 to .08 standard deviation increment in child cognitive ability. Quality is assessed using the Observational Record of the Caregiver Environment (ORCE).

¹⁸ 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 the existing data, as it requires three outcome observations and two lagged input observations. Even if feasible, this approach would entail a severe efficiency loss.

¹⁹ For Blau and Grossberg (1992), who use work experience prior to childbirth to instrument for maternal employment, compare columns 1 and 2 of their Table 2. For James-Burdumy (2005), who uses the percentage of the county labor force employed in services to instrument for maternal employment, compare columns FE and IV–FE from her Table 3. Note that, in the case of Blau and Grossberg (1992), it is also questionable if work prior to childbirth is uncorrelated with the child ability endowment (as it is likely correlated with mother's ability).

List of instruments.	
Variable	Description
Time limits	
TLI _{st} TL_LENGTH _{st} TL_HIT _{ist} REMAIN_TL_ELIG _{ist} REMAIN_CAT_ELIG _{ist}	Dummy for whether State s has time limit in place in period t Length of time limit in State s in period t Dummy variable indicating whether a woman would have hit time limit Minimum potential remaining length of a woman's time limit, constructed: TL_LENGTH _{st} – min{AGE_OLDEST_CHILD _{ist} , ELAPSED_TL _{st} } Remaining length of time to be categorically eligible for welfare benefits: 18-AGE_YOUNGEST_CHILD _{ist}
Work requirements	
DWR _{st} WR_LENGTH _{st} WR_HIT _{ist} AGE_CHILD_EXEM _{st} EXEMP _{st}	Dummy for whether State <i>s</i> has work requirement in place in period <i>t</i> . Length (in months) of work requirement limit in State <i>s</i> in period <i>t</i> . Indicator for whether a woman could be subject to a work requirement: = 1 if [WR_LENGTH _{st} \leq min{AGE_OLDEST_CHILD _{ist} , ELAPSED_WR _{st} } & AGE_YOUNGEST_CHILD _{ist} \geq AGE_CHILD_EXEM _{st}] Age of youngest child below which the mother will be exempted from work requirement in State <i>s</i> at time <i>t</i> Number of work requirement exemptions in State <i>s</i>
Earnings disregards	
FLAT _DISREGARD _{st} PERC _DISREGARD _{st}	Flat amount of earnings disregarded in calculating the benefit amount Benefit reduction rate (does not include phase-out)
Other policy variables	
BEN _{ist} EITC _{ist} CCDF _{st} ENFORCE _{st}	Real AFDC/TANF maximum benefits, calculated using the state (dollars) level benefit rule and the mother's family composition EITC phase-in rate constructed from both the federal and state level CCDF expenditure per single mother in State <i>s</i> at time <i>t</i> (\$thousands) Child support enforcement expenditure in State <i>s</i> at year <i>t</i> per single mother (\$thousands)
Local demand conditions	
UE _{st} SWAGE _{st} SERV _{st}	Unemployment rate in State <i>s</i> in period <i>t</i> Hourly wage rate at the 20th percentile of the wage distribution in State <i>s</i> in period <i>t</i> Percentage of the State <i>s</i> labor force employed in services in period <i>t</i>

ELAPSED_TL_{st}: time in months elapsed since the implementation of time limit. ELAPSED_WR_{st}: time in months elapsed since the implementation of work requirement.

3. Construction of instruments using welfare rules and other policy variables

To deal with the selection problem arising because children placed in childcare may differ systematically from those who are not, we use welfare policy rules as instruments (or exclusion restrictions) to help identify our selection model. Welfare rules have a large impact on labor supply of single mothers (see Moffitt (1992)). To construct our instruments, we collected very detailed information on State welfare policies. The working article version contains a detailed list of sources, and more detail on the construction of the instruments. Here, we briefly highlight the key aspects of Section 1115 welfare waivers and the 1996 welfare reforms (Personal Responsibility and Work Opportunity Reconciliation Act of 1996 or "PRWORA") relevant to this work. Table 1 presents the complete instrument list, including all policy variables. Each instrument has up to three subscripts: i for individual, s for State and t for period (quarter).

3.1. Benefit termination time limits

Under Aid to Families with Dependent Children (AFDC), single mothers with children under 18 were *entitled* to benefits, provided they met the income and asset screens. But under Section 1115 Waivers and Temporary Aid to Needy Families (TANF), States could set time limits on benefit receipt. Indeed, PRWORA forbids States from using federal funds to provide benefits to adults beyond a 60-month lifetime time limit, and it lets States set shorter limits (e.g., California imposes a 5-year limit, while Texas and Florida impose 2 –3 year limits).

Time limits have both direct and indirect effects. The direct effect is straightforward (i.e., when a woman hits the time limit she becomes ineligible). The indirect effect is subtler: forward-looking individuals should try to "bank" months of eligibility for later use. In the instrument list, we include five variables to capture these two effects of time limits (see Table 1). We include, e.g., a dummy

for whether a single mother's State of residence had imposed a time limit (TLI_{st}) at time t, a dummy for whether the time limit could possibly be binding (TL_HIT_{ist}) , and the maximum potential remaining time before hitting the time limit (*REMAIN_TL_ELIG*_{ist}). Note that we incorporate both time limits created under TANF and earlier under AFDC waivers.

We made a great effort to construct person specific instruments. For example, consider TL_HIT_{ist} . Say a woman resides in a State that imposed a 5-year time limit 6 years earlier. Then it is possible she could have hit the limit, provided her oldest child is at least 5. If her oldest child is less than 5, she cannot have participated in AFDC/TANF for 5 years, and so cannot have hit the limit. Thus, using data on ages of children, we can tailor the instrument to individual cases. Crucially, we do not use actual welfare participation histories to determine a woman's remaining eligibility, as participation is endogenous. We assume welfare rules and demographics (like ages and numbers of children) are exogenous (given controls for mother characteristics), so our individual specific instruments are functions of policy parameters and demographics alone.

3.2. Work requirement time limits and work requirement exemptions

Work requirements increase time costs of welfare participation. Under TANF, recipients must commence "work activities" within two years of coming on assistance to maintain benefits. But many States adopted shorter work requirement time limit clocks. Due to variation in when States implemented TANF, and in the length of their clocks, there is a substantial variation across States in how early single mothers could have hit binding work requirements. Also, States have the option to exempt single parents with children up to 1 year of age from work requirements, and to provide other exemptions as well. Thus, even within a State, there is variation across women in whether work requirements can be binding, based on age of the youngest child.

We construct five variables to measure work requirements (see Table 1). For example, *WR_HIT*_{ist}, is a dummy for whether a woman

could be subject to work requirements (based on her age, length of the time limit, time since the requirement was implemented, ages of children, etc.), and *AGE_CHILD_EXEM*_{st} is the young child exemption age in State *s* at time *t*.

3.3. AFDC/TANF benefit levels, earnings disregards and benefit reduction rates

AFDC/TANF benefits are determined by a formula whereby a State-specific grant level, increasing in the number of children under 18, is reduced by a fraction of a recipient's income. One variable we use to characterize the system is the maximum *potential* monthly AFDC/TANF benefit (*BEN*_{ist}), assuming zero income, constructed using the State grant level for the family size of the single mother. We put this variable in real terms using a region-specific CPI.²⁰

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

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

Starting in late 1992, many States obtained waivers to increase disregards. Under PRWORA, States may set their own disregard levels, and much heterogeneity has emerged. A few States expanded disregards and let them apply indefinitely. We code BRR and the percent disregard together in *PERC_DISREGARD*_{st}. Flat disregards are coded in *FLAT_DISREGARD*_{st}.

3.4. Child support enforcement

Child support is an important source of income for single mothers, despite widespread non-payment.²¹ The Child Support Enforcement (CSE) program, enacted in 1975, pursues efforts to locate absent fathers and establish paternity. CSE expenditures greatly increased from \$2.9 billion in 1996 to \$5.1 billion in 2002. We use these expenditures as an indicator of CSE efforts. Specifically, we measure State level CSE activity by taking the State CSE expenditure and dividing it by the State population of single mothers (*ENFORCE*_{st}).

3.5. Childcare subsidies and the childcare and development fund (CCDF)

The CCDF is a block grant to States to provide subsidized childcare programs for low-income families. States have considerable autonomy, so a great deal of heterogeneity in program design has emerged. As an additional instrument, we use the State CCDF expenditure per single mother ($CCDF_{st}$) to capture the availability and generosity of childcare subsidies in a State.²²

3.6. Other instruments: Earned income tax credit (EITC) and local demand conditions

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

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

4. Structural and quasi-structural models

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

4.1. Overview of the structural model

Consider a woman making choices about work, childcare and welfare participation in each period *t* following the birth of a child, until the child goes to primary school at age 5. For expositional convenience, we consider a woman with a single child, and ignore additional fertility decisions (although we allow for multiple children in the empirical work). In our model, the time period is a quarter. We allow for three work options (full-time, part-time or no work), while the childcare and welfare choices are binary. As the option of working (either full-time or part-time) and not using childcare is infeasible, there are at most 8 alternatives in a woman's choice set. Of course, depending on the woman's state of residence and duration of welfare participation, her choice set will vary (e.g., a woman residing in a State with a 36 month welfare time limit would not have the option to receive welfare beyond 36 months). Formally, we denote the choice set as:

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

where h_t is work status (2 = full-time, 1 = part-time, 0 = no work), g_t is a dummy for welfare participation, and I_t^c is a dummy for use of childcare. J_{st} has both State (s) and time (t) subscripts due to variation in the welfare rules (e.g., a woman's duration of welfare receipt may make her eligible for welfare in one State and not another). It is also useful to define the choice indicator:

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

Next, we need to specify the current-period utility function given the choice of option *j*. Following Bernal (2008), a reasonable functional form would be:

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

 $^{^{20}\,}$ The BLS computes the CPI for 24 metropolitan areas and for four regions (west, south, midwest and northeast).

²¹ In 2002, child support accounted for approximately 6.5% of single mother's real incomes (March CPS).

²² We could instead use State program parameters, such as monthly income eligibility criteria, reimbursement rate ceilings or co-pay rates. We opt not to use these measures due to problems associated with rationing.

where the consumption c_t is given by the budget constraint:

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

The utility function (2) is CRRA in consumption, with parameter α_1 . Parameter α_2 is disutility from work. A_t is child cognitive ability; generated by a production function we define below. Mothers get utility from A_t according to a CRRA function with parameter λ , as in Bernal (2008). She estimated $\lambda < 1$, implying diminishing marginal utility from child ability. Then, mothers have an incentive to use time and goods to compensate children with low ability endowments.

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

The terms α_5 through α_9 in (2) capture various aspects of the utility/disutility from childcare use. These follow from Bernal (2008), who found they are necessary to fit data on childcare utilization well.²³ Parameter α_5 is a non-pecuniary benefit/cost associated with the use of childcare. α_6 is an extra cost of initiating childcare if one has not used it before. This may capture search time in finding a childcare center, and/or the psychic cost of first time separation from the child. α_7 is an extra cost from using childcare during the first quarter after birth (t = 1), and α_8 is an extra cost from using childcare before the child is one year old (t < 5). These parameters capture the fact that: (i) it is more difficult to find childcare centers that take infants, (ii) infant care is generally more expensive, and (iii) the psychic cost of separation from the child is greater when the child is very young. α_9 captures the fact that utility/disutility of childcare use may depend on whether childcare was used in the immediately preceding period.

Finally, ε_t^j is an alternative-specific random taste shock. FIML estimation would require a distributional assumption on these stochastic terms.²⁴ For example, we could assume that they are multivariate normal and independent over time. Since some alternatives are more similar than others, it would also be necessary to allow the ε_t^j to be correlated across alternatives.

Turning to the budget constraint (3), earned income is given by $w_t \cdot h_t \cdot (250)$ because we define part-time work (for a quarter) as 250 hours, and full-time as 500 hours. This grouping of hours facilitates estimation, as it keeps the choice set purely discrete. Keane and Moffitt (1998) adopted this approach to jointly model labor supply and welfare participation. They argued that grouping was desirable because hours are very concentrated at 20 and 40 per week, and much of the variation away from those figures is likely to be measurement error. The next term in the budget constraint, N_t , is non-labor income, which may include child support payments.

The third term (3) is $B(w_t, h_t, N_t, D_t, R_{st})$, the welfare benefit rule, which determines the benefit a woman receives if she participates in welfare (i.e., $g_t = 1$). This depends on the wage rate w_t , hours of work h_t , non-labor income N_t , the duration of previous welfare participation D_t , and a vector of State and time specific welfare rule parameters R_{st} .²⁵ One such parameter is the grant level a woman with no income receives. This differed

has only one child. But, in reality, welfare benefits also depend on the number of children, a fact that we will account for later.

greatly across States and time even under AFDC. Under TANF and waivers, substantial heterogeneity across States has also emerged in the rate at which benefits are reduced if a woman has earned or unearned income. Duration of prior welfare participation also matters for benefits, as some States eliminate or reduce the benefit by a proportion when a critical level of duration is reached (e.g., in California the benefit is reduced, but not eliminated, after 5 years). Such features are captured in R_{st} .

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

Besides the budget constraint, a woman faces two other constraints that influence work and childcare decisions: a wage function and the child cognitive ability production function. To explain these, it is useful to define w_o as a woman's "initial wage", prior to giving birth. This is the observed wage for an employed woman, or a latent offer wage for non-workers. We model the initial wage as a function of a woman's observed and unobserved characteristics as follows:

$$\ln w_o(\mu_w) = \mu_w + \theta_1 educ + \theta_2 age + \theta_3 age^2 + \theta_4 race + \theta_5 AFQT + \bar{\theta}_6 \tau_{s,o} + v_{wo}.$$
(4)

Here, μ_w represents *unobserved* heterogeneity in mothers' skill endowments. The variables education (*educ*), *race* (an indicator for non-white), and *AFQT* capture *observed* heterogeneity in the skill endowment, while *age* (i.e., age at the time of child birth) captures movement along the life-cycle wage path. The vector $\tau_{s,o}$ is a set of local demand conditions in a woman's State of residence, and $\bar{\theta}_6$ is the associated parameter vector. Finally, ν_{w0} captures transitory shocks to income and/or measurement error, which we assume are serially independent. FIML would require a distributional assumption on ν_{w0} , such as $\nu_{w0} \sim N(0, \sigma_w^2)$.²⁶

It is useful to define $\ln w_0(\mu_w) = \ln \bar{w}_0(\mu_w) + \bar{\theta}_6 \tau_{s,o} + \nu_{w0}$ so that $\ln \bar{w}_0(\mu_w)$ represents the persistent part of the woman's log offer wage at the time of childbirth. Then, after childbirth, the wage a woman can earn upon returning to work is given by the following process:

$$\ln w_t(\mu_w) = \ln \bar{w}_0(\mu_w) - \delta \cdot t + \phi_1 E_t + \phi_2 f_{t-1} + \phi_3 p_{t-1} + \phi_4(E_t \cdot educ) + \bar{\theta}_6 \tau_{st} + v_{wt}.$$
(5)

Here, δ is the depreciation rate of human capital, and $\delta \cdot t$ captures the percentage depreciation of a woman's offer wage if she leaves the labor force for t periods after childbirth. Acquiring work experience counteracts this depreciation. $E_t = \sum_{\tau=0}^{t-1} h_t$ is the total work experience since birth, f_{t-1} and p_{t-1} indicate whether a woman worked full-time or part-time in the preceding period, and $E_t \cdot educ$ is an interaction between experience and education. The vector τ_{st} is the set of local demand conditions in the woman's State of residence in period t after childbirth, and θ_6 is the associated parameter vector. Finally, v_{wt} is a stochastic term due to transitory shocks to productivity and/or measurement error. Again, FIML would require a distributional assumption on v_{wt} in order to solve the dynamic optimization problem and form the likelihood function (e.g., $v_{wt} \sim N(0, \sigma_w^2)$).

Next, we describe the child cognitive ability production function. We assume a child is born with a cognitive ability endowment A_o . This endowment is correlated with a set of observable variables,

170

 $^{^{23}}$ The exception being the interaction between current and lagged childcare, which she did not need to include.

 ²⁴ Note that a distributional assumption is necessary not only to form the likelihood function, but also to solve the agent's dynamic optimization problem.
 ²⁵ Recall that in writing the model we are assuming, for simplicity, that the woman

 $^{^{26}}$ A distributional assumption is needed for FIML or quasi-structural estimation, but can be avoided in IV or MOM.

and also contains an unobservable component, as follows:

$$\ln A_{o}(\mu_{s}) = (\rho \mu_{w} + \mu_{k}) + \gamma_{1}AFQT + \gamma_{2}educ + \gamma_{3}race + \gamma_{4}age + \gamma_{5}age^{2} + \gamma_{6}I[age < 20] + \gamma_{7}I[age > 33] + \gamma_{8}EXPBEF + \gamma_{9}I[worked bef] + \gamma_{10}gender + \gamma_{11}BW = X\gamma + \mu_{s}.$$
(6)

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

Note that we control for mother's age at birth in a very flexible way by including *age*, age^2 and indicators for whether she was under 20 or over 33 (*I*[*age* < 20] and *I*[*age* > 33]). We do this because there is some evidence that children of teenage mothers (and older mothers) are less healthy and/or have worse cognitive test scores. However, there is also evidence that this association vanishes if one controls for mother's characteristics like education and income. Indeed, we find below that age is completely insignificant in the production function.²⁷

We emphasize that the coefficients γ_1 through γ_{11} in (6) do not capture causality, but merely *correlation* between observables and the child's cognitive ability endowment. It is desirable to let observables "sop up" as much of the child's unobserved ability endowment as possible, as this should reduce the sensitivity of our results to the distributional assumptions we place on the unobserved heterogeneity terms. Indeed, if we could perfectly control for the skill endowment using observed correlates, the selection problem in estimating the impact of maternal time on child outcomes would vanish. This logic applies to any method used to estimate the effect of maternal time, whether it be single equation IV, quasi-structural estimation, or FIML.

Finally, we turn to the cognitive ability production function itself. This captures the notion that the child's initial ability endowment, A_o , interacts with subsequent inputs—maternal time (T), childcare (C) and goods (G)—to determine the child's cognitive ability at age t, denoted A_t . We start with a specific version of Eq. (2), in which A_o enters explicitly, and in which only cumulative inputs matter.²⁸ Dropping the mother and child subscripts, we write:

$$\ln A_t(\mu_s) = \ln A_o(\mu_s) + \gamma_{12} \widehat{T}_t + \gamma_{13} \widehat{C}_t + \gamma_{14} \ln \widehat{G}_t + \eta_{st}.$$
 (7)

Here, \hat{T}_t denotes the cumulative input of maternal time through age t, \hat{C}_t denotes cumulative input of alternative caregivers' time,

and \hat{G}_t denotes cumulative input of goods. It is convenient to let goods enter in log form, for reasons that will become clear shortly. Comparing (1) with (7), the term $\alpha_4 X_t + \mu + \delta$ (i.e., the ability endowment) has been subsumed in $\ln A_o(\mu_s)$. And, we replace ε with η_s because the dependent variable in (7) is actual ability rather than a noisy measurement, so η_s captures only shocks to the development path. In (7), we assume homogeneous coefficients on time and goods inputs. This is expositionally convenient for the remainder of this section, but we will allow for heterogeneous coefficients in Section 4.2.

As *T* and *G* are not directly observed, we need assumptions relating them to observables to obtain an estimable equation. First, consider the maternal time input. One could imagine a model where mothers decide how much "quality" time to devote to the child while at home (e.g., children's time is divided between childcare, "quality" time with the mother, and time spent watching TV while the mother does housework). But, since we do not observe the actual contact time between mothers and children (let alone the subset that is "quality" time),²⁹ we simply sidestep the issue by assuming $T_{it} = T - C_{it}$, where *T* is total time in a period. Thus, we distinguish between only two types of time–time with the mother and time in childcare. Then we can rewrite (7) as:

$$\ln A_{t}(\mu_{s}) = \ln A_{o}(\mu_{s}) + (\gamma_{12}T) \cdot t + (\gamma_{13} - \gamma_{12})C_{t} + \gamma_{14} \ln \widehat{G}_{t} + \eta_{st}$$
(8)

where $T \cdot t$ and \hat{C}_t arise from adding $T - C_{it}$ over t periods. Eq. (8) clarifies that we can only really estimate $\gamma_{13} - \gamma_{12}$, the effect of time in childcare *relative* to the effect of mother's time.

Next, consider the goods input *G*, which is also largely unobserved. For example, the NLSY contains information on books in the home, but lacks other potentially important goods inputs like nutrition, health care, tutors, etc. To appreciate the implications of this, suppose the decision rule for cumulative monetary investment (in the form of goods) in child ability (conditional on work, income and childcare usage decisions) is given by:

$$\ln \hat{G}_{it} = \pi_0 + \pi_1 X_i + \pi_2 \mu_{si} + \pi_3 \hat{C}_{it} + \pi_4 \ln \hat{I}_{it}(W, H; R) + \pi_5 t + \varepsilon_{it}^g.$$
(9)

This is a conditional decision rule, obtained as the second stage in an optimization process, where, in stage one, a mother chooses childcare inputs and hours of market work. The notation $\widehat{I}_{it}(W, H; R)$ highlights the dependence of cumulative income on histories of wages W, market work hours H, and welfare rules R that govern how benefits depend on income. Eq. (9) can be viewed as a simple linear approximation to the more complex decision rule generated by the dynamic model. It captures the notions that: (i) mothers' decisions about goods inputs may be influenced by (i.e., made jointly with) decisions about work and childcare, and (ii) inputs depend on the observed mother and child characteristics X, and on the child ability endowment μ_{si} . The time trend in (9) captures growth of cumulative inputs over time. The stochastic term, ε_{it}^g , captures mothers' idiosyncratic tastes for investment in the form of goods.³⁰

Now, substituting (9) and (6) into (8), we obtain (suppressing the *i* subscripts):

$$\ln A_t(\mu_s) = \ln A_o(\mu_s) + (\gamma_{12}T) \cdot t + (\gamma_{13} - \gamma_{12})\hat{C}_t + \gamma_{14}[\pi_0 + \pi_1 X + \pi_2 \mu_s + \pi_3 \hat{C}_t + \pi_4 \ln \hat{\Gamma}_t + \pi_5 t + \varepsilon_t^g] + \eta_{st}$$

= $\gamma_{14}\pi_0 + (\gamma_{12}T + \gamma_{14}\pi_5) \cdot t + (\gamma_{13} - \gamma_{12} + \gamma_{14}\pi_3)\hat{C}_t$

²⁷ If age mattered in the production function, and we did not control it, it would threaten the validity of our welfare policy instruments. These policy rules are correlated with mother's age at childbirth, because the teenage mothers in the NLSY79 cohort had children too early to be affected by TANF or waivers. For evidence on the effect of maternal age on child outcomes, see, e.g., Lopez (2003), Geronimus et al. (1994) and Bernal and Keane (2008).

²⁸ A general functional form, where inputs at age *t* may differentially effect ability at each age *t'* and μ_s may have different effects at each age, is infeasible due to proliferation of parameters. We adopt the simplification, familiar from the human capital literature, that: (i) only cumulative inputs matter, and (ii) the effect of the permanent unobservable is constant over time. Similarly, in a typical Mincer earnings function, only cumulative education and experience affect human capital, and the unobserved skill endowment has a constant effect on log earnings.

 $^{^{29}}$ The NLSY's "HOME" environment index contains such variables as how often the child is read to, eats meals with the parents, etc., but it is not sufficiently comprehensive to measure the total maternal quality time input.

³⁰ This may arise due to heterogeneous preferences for child quality.

$$+ \gamma_{14}\pi_{4} \ln I_{t} + X(\gamma + \gamma_{14}\pi_{1}) + (1 + \gamma_{14}\pi_{2})\mu_{s} + \gamma_{14}\varepsilon_{t}^{g} + \eta_{st} = \beta_{0} + \beta_{1} \cdot t + \beta_{2}\widehat{C}_{t} + \beta_{3} \ln \widehat{I}_{t} + X\beta_{4} + \hat{\mu}_{s} + \hat{\varepsilon}_{t}^{g} + \eta_{st}.$$
(10)

Eq. (10) is estimable, as all independent variables are observable. However, we must be careful about the appropriate estimation method and interpretation of results. As we have stressed, childcare use may be correlated with the unobserved part of a child ability endowment μ_s . It may also be correlated with ε^g , the mother's taste for goods investment (i.e., if these tastes are correlated with tastes for childcare use, as seems plausible).³¹ Thus, for welfare rules R_{st} and local demand conditions τ_{st} to be valid instruments for estimating (10), they must be uncorrelated with both μ_s and ε^g , which we view as a plausible exogeneity assumption.^{32, 33}

Cumulative income may also be endogenous in (10), for multiple reasons. First, income depends on the jointly made childcare and work decisions. Hence, it is potentially correlated with child ability for the same reasons as are operative for childcare use. Second, income depends on the mother's wage rate, which depends on her unobserved ability endowment. If this is correlated with the child ability endowment (i.e., $\rho \neq 0$ in (6)), it also generates correlation between income and μ_s . Thus, we need to instrument for income as well. Again, we argue that the welfare rules R_{st} and local demand conditions τ_{st} provide plausible instruments, as they have important effects on work decisions, yet it is plausible that they are uncorrelated with child ability endowments.

Even assuming we obtain consistent estimates of (10), it is still important to recognize that the childcare "effect" we estimate is $\beta_2 = \gamma_{13} - \gamma_{12} + \gamma_{14} \cdot \pi_3$. This is the effect of childcare time (γ_{13}) *relative* to mother's time (γ_{12}), plus the effect of any change in goods inputs that the mother chooses because of using childcare ($\gamma_{14} \cdot \pi_3$). In light of this, it is important to understand the limitations of estimates of (10). For instance, such estimates cannot predict how a policy like a childcare subsidy would affect child outcomes. Such subsidies would not only alter childcare use, but also the budget constraint conditional on I_{it} , and I_{it}^c , and hence the decision rule for goods inputs (9). Thus, it may alter goods inputs in a way not captured by $\gamma_{14} \cdot \pi_3$. The problem arises because, while γ_{12} , γ_{13} , and γ_{14} are structural parameters of the production technology, the reduced form parameter π_3 in the decision rule for goods is not policy invariant.

Thus, in interpreting our estimated effects of childcare on child cognitive outcomes, one must be careful to view them as applying only to policies that do not alter the decision rule for goods investment in children (9). As this decision rule is conditional on work, income and childcare decisions, it will be invariant to policies that leave the budget constraint conditional on those decisions unchanged. A work requirement that induces a woman to work and use childcare, but that leaves her wage rate and the cost of care unaffected, would fall into this category.

We have used a very simple form for (10) to clarify estimation issues, but we will adopt more general production functions in our empirical work. For instance, we include interactions between the child's initial (latent) ability and household inputs, to allow the effect of inputs to vary depending on the type of the child.³⁴ Bernal (2008) found that returns to maternal time in production of child cognitive ability are greater for children with higher initial skill endowments.

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

$$\ln S_t = \ln A_t(\mu_s) + \eta_1 d_{1t} + \eta_2 d_{2t} + \eta_{st}^*$$
(11)

where d_{1t} and d_{2t} are test dummies (i.e., PIAT or PPVT) to capture mean differences across the tests (see Section 5). The term η_{st}^* is measurement error, and we would need a distributional assumption such as $\eta_{st}^* \sim N(0, \sigma_n^2)$.

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

A key issue in structural estimation is what mother's know, as this affects how they solve their dynamic optimization problem. For example, Bernal (2008) assumed mothers know the cognitive ability endowment of their child, but that it is unobserved by the econometrician. While assuming mothers know more than econometricians is reasonable, the assumption that they have complete information may be extreme. Hence, one might consider alternative formulations where μ_s is split up into components the mother does and does not observe. Again, explicit assumptions on this issue can be avoided in IV or quasi-structural estimation, but proper estimation methods and interpretation of results will depend on one's implicit assumptions.³⁵

Structural estimation also requires assumptions regarding what mothers know about the cognitive ability production function, the wage equation, and the welfare rules. If mothers understand each of these, then there are three key sources of dynamics in the model. Mothers know: (i) how their decisions about working after childbirth affect the evolution of their human capital, according to Eq. (5), (ii) how their decisions about work and childcare affect cognitive ability outcomes for their child (as determined by Eq. (9)), and (iii) how welfare participation decisions affect future welfare eligibility, future choice sets and future budget constraints (when there are termination, work requirement and/or benefit reduction time limits).

Again, non-structural approaches would make implicit assumptions in these areas. For instance, a child fixed effects estimator implicitly assumes that mothers are not learning about child ability

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

³² To our knowledge, it has not been previously noted that consistent estimation of an equation like (9) requires instruments that are uncorrelated with both μ_s and the mother's tastes for goods investment in the child, $\varepsilon^{\rm g}$.

³³ The instruments must also be uncorrelated with the contemporaneous shock to the child development path, η_{st} , which seems uncontroversial. FIML requires a distributional assumption on the composite error, $\hat{\varepsilon}_t^g + \eta_{st}$, whose components cannot be separated.

³⁴ As the child's initial ability endowment is partly determined by the genetic endowment, these interactions capture the notion that genetic endowments interact with environment influences (inputs) to determine cognitive outcomes.

³⁵ For example, OLS and sibling fixed effects estimators implicitly assume that mothers do not know the cognitive ability endowments of their children. If mothers do know μ_{s} , it creates an important potential source of bias in such estimates of the cognitive ability production function. For instance, if mothers compensate low endowment children by spending more time with them (and using childcare less), this will upward bias OLS estimates of the effect of childcare on cognitive development. This problem cannot be dealt with by use of sibling fixed effects estimators, because, if mothers can see the endowment differences across their children, they may treat them differently.

itself, or the form of the cognitive ability production function, as test scores are realized. If they were, the shock to the time t test score would affect inputs between time t and time $t + 1.^{36}$ Thus, the strict exogeneity assumption of the fixed effects estimator is violated.

Structural estimation also involves assumptions on how unobserved heterogeneity enters the model. We have already specified that there is unobserved heterogeneity in mother and child ability endowments (μ_w and μ_s , respectively). FIML requires an assumption on their joint distribution. Typically, additional heterogeneity is required to fit the data. For instance, a typical specification would allow mothers to be heterogeneous in tastes for work (α_2), tastes for welfare participation (α_4), and tastes for childcare utilization (α_5).

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

Each woman also has a set of individual specific state variables that stay fixed over time, or that evolve exogenously. These are: (i) her child's cognitive ability endowment, gender, and birthweight, and (ii) her skill endowment, age, education, race, AFQT score, whether and how much she worked prior to childbirth, and number of children, and (iii) her State-specific welfare policy rules, childcare subsidy parameters and local labor demand conditions. (Crucially, in Section 4.2, when we set up the quasi-structural approximation to the model, we must be careful to include all the state variables—both those in Ω_t and those that are individual specific.)

A final issue is that the choice problem changes fundamentally when a child reaches roughly age 5, and he/she begins kindergarten. Then, childcare is no longer relevant (although after school care is still an issue). One strategy is to avoid modeling decisions beyond the time horizon of interest by specifying a terminal value function.³⁷ Then, FIML estimation of the structural model requires that, at any trial parameter vector, we solve an agent's dynamic programming (DP) problem numerically by "backsolving" from the terminal period *T* to t = 1. Then, we can form the joint probabilities of observed choices, wages and test scores conditional on observed states, and form the likelihood function. Both the DP solution and the likelihood evaluation would be extremely computationally burdensome in this case.

4.2. A quasi-structural approach: Approximate solution of the structural model

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

The decision rules for work and childcare should, in theory, be functions of all the state variables in our structural model. There is no basis for excluding any variables from these decision rules. For instance, any variable that affects wages, or child ability, must affect both work and childcare decisions in our model. Similarly, any variable that affects childcare decisions will affect work decisions, and vice versa. In contrast, the cognitive ability production function (10) and the wage equation (5) only depend on a subset of the state variables. Thus, our theoretical framework delivers exclusion restrictions to identify the selection model.

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

$$V_{f,t}^{*} = \beta_{0} + \beta_{1}age + \beta_{2}age^{2} + \beta_{3}educ + \beta_{4}race + \beta_{5}AFQT + \beta_{6}f_{t-1} + \beta_{7}E_{t} + \beta_{8}t + \bar{\beta}_{9}\tau_{st} + \beta_{10}BW + \beta_{11}gender + \beta_{12}I[age < 20] + \beta_{13}I[age \ge 30] + \beta_{14}EXPBEF + \beta_{15}workbef + \beta_{16}\hat{C}_{t} + \beta_{17}NC_{t} + \beta_{18}D_{t} + \beta_{19}I[\hat{C}_{t} = 0] + \beta_{20}I[t = 1] + \beta_{21}I[t < 5] + \beta_{22}I_{t-1}^{c} + \bar{\beta}_{23}R_{st} + \beta_{24}\theta_{st} + \varepsilon_{ft}^{*}.$$
(12)

Here, $\bar{\beta}_9$, $\bar{\beta}_{23}$, β_{24} are parameters that multiply the State/time specific local demand conditions, τ_{st} , welfare rules, R_{st} , and childcare spending, θ_{st} , whose important role in providing exclusion restrictions we stressed earlier. While we abstracted from multiple children in Section 4.1, here we include NC_t , the number of children younger than 18. Finally, we let $\varepsilon_{ft}^* = \mu_f + v_{ft}$, where μ_f is a permanent error component and v_{ft} is a transitory error component.

The linear approximation to the value function for part-time work is similar, except it has coefficients that go from β_{25} to β_{49} and a stochastic term $\varepsilon_{pt}^* = \mu_p + v_{pt}$.³⁸ Then, normalizing the value function for No-Work to 0, and assuming that v_{ft} and v_{pt} are jointly normally distributed, we obtain a multinomial probit (MNP) model. In forming the likelihood function, we simulate the MNP choice probabilities using the GHK probability simulator (see Keane (1994)).

Similarly, the decision rule for childcare is approximated by a probit where the value function for use of childcare V_c^* is a linear function of all the state variables, with associated coefficients β_{50} to β_{75} and a stochastic term $\varepsilon_{ct}^* = \mu_c + v_{ct}$.

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

$$\ln S_{t} = \ln A_{o}(\mu_{s}) + \beta_{76}C_{t} + \beta_{77}(C_{t} \cdot \ln A_{o}(\mu_{s})) + \beta_{78}I_{t} + \beta_{79}(\widehat{I}_{t} \cdot \ln A_{o}(\mu_{s})) + \beta_{80} \cdot t + \beta_{81}NC_{t} + \beta_{82}d_{1t} + \beta_{83}d_{2t} + v_{st}$$
(13)

³⁶ This is true if work/childcare choices depend on perceived child ability. For instance, suppose mothers compensate low ability children by spending more time with them. Then, a negative shock to the test score at time *t* (which is part signal and part noise) would cause an increase in maternal time (i.e., reduction in work and childcare) between *t* and *t* + 1. Using fixed effects or first-difference estimators, thus induces a negative bias in estimates of the 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 childcare use fall).

³⁷ For instance, Bernal (2008) models a mother's decisions from t = 1, the first quarter after childbirth, until t = 20. At T = 21, she assumes a terminal value function that is a flexible function of the state variables. In the present case, we could write $V_T(\Sigma_T) = P(A_T, E_T, D_T)$ where $P(\cdot)$ denotes a flexible polynomial function. In this terminal value function, the woman cares about the cognitive ability of her child, her own work experience (which will affect her future earning capacity) and her accumulated welfare usage at time T = 21 (which affects her eligibility for future benefits).

³⁸ The only difference is that V_f^* depends on lagged full-time, while V_p^* depends on lagged part-time. Keane (1992) shows that error correlations in the MNP are practically impossible to identify without such exclusion restrictions. Nevertheless, the probability of full- and part-time work in the model are functions of all the state variables.

where $v_{st} = \eta_{st} + \eta_{st}^*$ (i.e., shocks to the development path plus measurement error), and:

$$\ln A_{o}(\mu_{s}) = \beta_{84} + \beta_{85} AFQT + \beta_{86} educ + \beta_{87} race + \beta_{88} age + \beta_{89} age^{2} + \beta_{90} BW + \beta_{91} I[age < 20] + \beta_{92} I[age > 33] + \beta_{93} gender + \beta_{94} EXPBEF + \beta_{95} I[workedbef] + \mu_{s}.$$

We define $\varepsilon_{st}^* = \mu_s + v_{st}$. Recall that A_o is the child's initial skill endowment, of which μ_s is the unobserved component. d_1 and d_2 are test dummies, for PPVT or PIAT-Math. Note that (13) includes interaction terms between inputs and the ability endowment that we mention in Section 4.1 but did not include explicitly in Eqs. (7)–(8) and (10) to simplify the exposition.³⁹ This allows for heterogeneity in effects of childcare and income on child outcomes. Table 2 summarizes the control variables we include in the child cognitive ability production function.

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

$$\ln w_{0} = \beta_{96} + \beta_{97}educ + \beta_{98}age + \beta_{99}age^{2} + \beta_{100}race + \beta_{101}AFQT + \bar{\beta}_{102}\tau_{so} + \varepsilon_{w0}^{*}$$
(14)
$$\ln w_{t} = \beta_{96} + \beta_{97}educ + \beta_{98}age + \beta_{99}age^{2} + \beta_{100}race + \beta_{101}AFQT + \bar{\beta}_{102}\tau_{st} + \beta_{103} \cdot t + \beta_{104}E_{t} + \beta_{105}f_{t-1}$$

$$+\beta_{106}p_{t-1}+\beta_{107}(E_t \cdot educ)+\varepsilon_{wt}^*$$

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

We assume that the permanent error components { μ_f , μ_p , μ_c , μ_s , μ_w } have a joint normal distribution $F(\mu)$. Allowing correlation of the time invariant unobservables across the four equations of the system (i.e., the MNP for work, the probit for childcare, the wage equation and the test score equation) is the mechanism through which joint estimation corrects for selection bias. In contrast, the time varying errors { ν_{ft} , ν_{pt} , ν_{ct} , ν_{st} , ν_{wt} } are assumed independent normal. To achieve identification of the work and childcare probits, we constrain the variances of ε_{ft}^* and ε_{ct}^* to 1. From this setup, it is easy to see the exclusion restrictions

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

The structure of the model delivers additional exclusion and functional form restrictions, because the decision rules for work and childcare must depend on all the state variables, while some are excluded from the wage and cognitive ability production functions by the structural assumptions. For example, lagged full- and part-time work, as well as work experience, enter the decision rules for work and childcare because they affect offer wages (Eq. (5)). But they do not enter the child cognitive ability production function directly. In our structure, the assumed inputs to the production function are: (i) cumulative time that the child spends with alternative care providers rather than the mother, and (ii) the mother's cumulative income since childbirth. Thus, total work experience and lagged full- and part-time work affect cognitive outcomes only through

their effects on (i) and (ii). This exclusion restriction is delivered by the structure. Similarly, cumulative welfare participation (D_t) enters the decision rules for work and childcare because it affects incentives to work and/or participate in welfare. But under our structural assumptions it is excluded from entering the cognitive ability production function (or the wage function) directly.

Of course, an alternative to the quasi-structural model described here is the simpler single-equation IV approach; estimate the cognitive ability production function alone, using instruments for cumulative income and childcare. As the sequential choice model is not made explicit, the instruments must capture average incentives to work and use childcare from birth up to time *t*. For instance, one might somehow average the welfare rule parameters over the period, or use many lagged values. In Bernal and Keane (2008), we try various different approaches to this problem.

Finally, it is worth emphasizing that using the data on women with multiple children is rather difficult in a fully structural approach, for reasons we discussed earlier (i.e., one needs to model how the mother allocates time and income among children). But in quasi-structural or linear IV approaches, it is simple to include the main effect of number of children in the test score and other equations of the system, as well as interacting \hat{I}_t and \hat{C}_t with number of children to allow the effects of income and childcare to depend on the number of children. Prior non-structural work in this area has generally not discussed this issue, or included such interactions. We will experiment with these interactions below.⁴⁰ A related point is that prior non-structural work has generally included married and single women in the same sample when estimating the effects of maternal time or childcare on child outcomes. Clearly, the assumption that marital status does not substantially alter the relationships of interest is guite strong, as it fundamentally alters the work decision.

5. National longitudinal survey of youth data

5.1. Individual level data

We use data from the NLSY 1979 youth cohort (NLSY79). This consists of 12,686 individuals, approximately half of them women, who were 14–21 years of age as of January 1, 1979. It includes a core random sample and over-samples of blacks, Hispanics, poor whites and the military. Interviews have been conducted annually from 1979 through 1994, and biannually since 1994. The NLSY79 has regularly collected pre- and postnatal care information from the sample women as they became mothers. In 1986, a separate survey of all children born to NLSY79 female respondents began. The child survey includes a battery of child cognitive, socioemotional, and psychological well-being questions/tests that are administered biennially for children of appropriate age.

Using the NLSY79 Workhistory File, we construct a detailed employment history for each mother in the sample for the period surrounding the birth of her child, i.e., up to four quarters before birth and each quarter interval after the child's birth for a period of five years. We use the geocode data to identify the State of residence of each individual in order to be able to construct Statespecific welfare rule parameters and measures of local demand conditions.

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

⁴⁰ The number of children may itself be endogenous if there is a quality/quantity tradeoff. In an IV approach, one can instrument for number of children and its interaction terms, as in Bernal and Keane (2008). Our model deals with this through correlation among the μ 's. E.g., if women with many children tend to have low skill endowments, they will tend to have low μ 's in the wage equation.

Table 2Control variables in the cognitive ability production function.

Variable	Description
Vallable	Description
Baseline specification	
EDUC _i	Mother's educational attainment at childbirth
AFQT _i	Mother's AFQT score
I[AFQTmissing] _i	Dummy for whether AFQT score is missing
AGE _i	Age of the mother at childbirth
AGE_i^2	Age of the mother at childbirth squared
$I[AGE_i < 20]$	Dummy for whether mother is younger than 20 years old
$I[AGE_i >= 33]$	Dummy for whether mother is older than 33 years old
I[workbef] _i	Dummy for whether mother worked prior to childbirth
EXPBEF _i	Mother's total work experience (in number of years) prior to childbirth
NSIB _i	Number of siblings
RACE _i	Child's race (1 if black/hispanic, 0 otherwise)
GENDER _i	Child's gender (1 if male, 0 if female)
BW_i	Child's birthweight (ounces)
AGECHILD _i	Child's age at assessment date
dPPVT _i	Dummy for whether the corresponding test is PPVT
dMATH _i	Dummy for whether the corresponding test is PIAT-MATH
Alternative specifications also include	
$C_{ti} * \ln A_{oi}$	Cumulative childcare use interacted with child's initial skill endowment
$I_{ti} * \ln A_{oi}$	Cumulative household income interacted with child's initial skill endowment
$C_{ti} * EDUC_i$	Cumulative childcare use interacted with mother's education
$I_{ti} * EDUC_i$	Cumulative household income interacted with mother's education

Table 3Exclusion restrictions in the model.

Variable	Description	Full-time decision	Part-time decision	Childcare decision	Wage equation	Cognitive ability production function
age	Age of mother at childbirth	Х	Х	Х	Х	Х
age ²	Age squared	Х	Х	Х	Х	Х
education	Mother's education at childbirth	Х	Х	Х	Х	Х
race	Child's race	Х	Х	Х	Х	Х
f_{t-1}	$I[workedfull - time_{t-1}]$	Х		Х	Х	
p_{t-1}	$I[workedpart - time_{t-1}]$		Х	Х	Х	
AFQT	Mother's AFQT	Х	Х	Х	Х	Х
AFQT missing	I[Mother's AFQT missing]	Х	Х	Х	Х	Х
Et	Mother's work experience	Х	Х	Х	Х	
t	Time trend	Х	Х	Х	х	Х
UE	Unemployment rate	х	Х	Х	х	
SWAGE20	Average wage 20th percentile	Х	Х	Х	Х	
SERV	% employment in services	Х	Х	Х	Х	
BW	Birthweight	х	Х	Х		Х
gender	Child's gender	Х	Х	Х		Х
NSIB	Number of siblings	Х	Х	Х		Х
<i>I</i> [age < 20]	<i>I</i> [mother's age <20]	Х	Х	Х		Х
<i>I</i> [age > 33]	I[mother's age > 33]	Х	Х	Х		Х
EXPBEF	Experience before childbirth	Х	Х	Х		Х
workbef	I[worked before childbirth]	Х	Х	Х		Х
Ct	Cumulative childcare	Х	Х	Х		Х
It	Cumulative income					Х
d_1, d_2	Test dummies					Х
$I[C_t > 0]$	<i>I</i> [Cumulative childcare > 0]	Х	Х	Х		
D_t	Cumulative welfare	Х	Х	Х		
I[t = 1]	I[t = 1]	Х	Х	Х		
I[t < 5]	I[t < 5]	Х	Х	Х		
I_{t-1}^c	Previous period childcare choice	Х	Х	Х		
DEN	Walfara hanafita	v	v	v		
DEIN ITTL on DIA/D1	Time Limit or Mork Dequirement	A V	A V	X		
	Time limit longth	A V	A V	X		
IL_LENGIH	The M/D might have hit	A V	A V	X		
WR HIT	IL OF WK HIIGHT HAVE HIT	Λ	A	A		
REMAIN THELIC	Remaining months of TL eligibility	x	x	x		
REMAIN FLIC	Remaining categorical eligibility	x	x	x		
WR I FNGTH	Work requirement length	X	X	X		
ACE EXEM	Age of youngest child exemption	X	X	X		
FXFMP	Number of WR exemptions	X	X	X		
FLAT DIS	Flat earnings disregard	X	X	X		
PERC DIS	Percent earnings disregard	X	X	x		
FNFORCE	Child support enforcement	X	x	X		
LINORCE	expenditure		~	~		
FITC	FITC phase-in rate	х	х	x		
CCDF	CCDF expenditures	X	x	x		
CCDI	cept experiances	Λ	Λ	Λ		

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

Estimation of the quasi-structural model of Section 4.2 requires a sample of women that are single (i.e., who did not cohabitate with a male) during five years following child birth, and for whom we observe at least one child test score. About 1464 mothers in the NLSY satisfy these requirements, and we have 3787 test score observations on their children.

Of these women, 245 had children between 1990 and 2000, so waivers and TANF impact their labor supply/childcare decisions before the children reach school age. Much of our leverage for identification comes from comparing outcomes for these children with outcomes for the 1219 children born too early for their mothers' behavior to be impacted by welfare reform. However, even in the pre-reform period some of our instruments, like AFDC grant levels and local demand conditions, varied greatly across States and over time, also providing an important source of identification. And, in the post-reform period, we also get leverage for identification by comparing children in States with "strict" vs. "lenient" welfare rules.⁴¹

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

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

5.2. Maternal time inputs, income and child assessments

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

Thus, we use the childcare indicator, in conjunction with work history data, to construct: (i) a dichotomous indicator of childcare



Fig. 1. Employment and childcare choices of single mothers after birth (NLSY).

use, the dependent variable in the childcare probit, and (ii) a measure of full-time, part-time or no childcare use, which we use to construct the cumulative childcare measure that appears in the cognitive ability production function (14).

Specifically, if a woman reported using at least 10 h per week of childcare, she is assumed to have used childcare during the quarter.⁴³ If she worked full-time (375+ hours in the quarter) we assume childcare must have been full-time (which seems clear). On the other hand, if the mother did not work (<75 hours in the quarter) but reported using childcare, it seems highly likely the childcare was only part-time. More difficult is making a reasonable assignment if the mother worked part-time (75-375 hours in the quarter). We decided to assume the childcare was part-time in this case. We admit that this assignment is not obvious. However, if we assign full-time childcare in this case it has almost no effect on our results. Thus, we define the function:

$$h_t^c = \begin{cases} 1 & \text{if mother works full-time and used childcare} \\ 0.5 & \text{if mother works part-time and used childcare} \\ 0.5 & \text{if mother did not work and used childcare} \\ 0 & \text{otherwise} \end{cases}$$
(15)

and form cumulative childcare, \hat{C}_t , and current childcare, I_t^c , as follows:

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

where *t* is the age of the child.

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

Another input in the child cognitive ability production function (14) is real household income. We measure it by summing income from all sources including wages, public assistance, unemployment benefits, interest or dividends, pension, rentals, alimony,

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

⁴² In '82, '83 and '84, mothers were asked how many hours the youngest child was in childcare. But there is a serious missing data problem (e.g., only 115 of the 1464 mother-child pairs in our sample have non-missing data in 1982).

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

R. Bernal, M.P. Keane / Journal of Econometrics 156 (2010) 164-189

Table 4
Mean characteristics of mothers in the sample.

All mothers in NLSY	Single mothers at childbirth only	Single mothers for 5 years after childbirth	Our sample
24.8	23.56	23.80	23.13
(5.56)	(5.07)	(5.15)	(4.59)
12.0	11.3	11.3	11.2
(2.475)	(1.920)	(1.917)	(1.909)
37.9	21.7	19.9	19.3
(27.23)	(20.09)	(19.11)	(18.30)
0.47	0.73	0.79	0.83
(0.499)	(0.445)	(0.404)	(0.379)
6.32	4.74	4.90	4.39
(7.71)	(8.23)	(9.85)	(2.01)
2.9	3.1	3.1	3.1
(1.37)	(1.57)	(1.61)	(1.53)
0.55	-	-	-
(0.004)			
4814	2528	1820	1464
3274	1620	1102	941
	All mothers in NLSY 24.8 (5.56) 12.0 (2.475) 37.9 (27.23) 0.47 (0.499) 6.32 (7.71) 2.9 (1.37) 0.55 (0.004) 4814 3274	All mothers in NLSYSingle mothers at childbirth only 24.8 23.56 (5.56) (5.07) 12.0 11.3 (2.475) (1.920) 37.9 21.7 (27.23) (20.09) 0.47 0.73 (0.499) (0.445) 6.32 4.74 (7.71) (8.23) 2.9 3.1 (1.37) (1.57) 0.55 $ (0.004)$ 4814 2528 3274 1620	All mothers in NLSY Single mothers at childbirth only Single mothers for 5 years after childbirth 24.8 23.56 23.80 (5.56) (5.07) (5.15) 12.0 11.3 11.3 (2.475) (1.920) (1.917) 37.9 21.7 19.9 (27.23) (20.09) (19.11) 0.47 0.73 0.79 (0.499) (0.445) (0.404) 6.32 4.74 4.90 (7.71) (8.23) (9.85) 2.9 3.1 3.1 (1.37) (1.57) (1.61) 0.55 - - (0.004) 3228 1820 3274 1620 1102

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

child support and/or transfers from family or relatives. Household income is deflated using a region-specific CPI, just as we did for welfare benefits (see Section 3.4), to account for differences in costs of living across metropolitan areas. We then construct cumulative real income since childbirth.

The NLSY79 cognitive ability measures that we use as the dependent variable in (14) are the Peabody Picture Vocabulary Test (PPVT) at ages 3, 4 and 5, and the Peabody Individual Achievement Test Reading Recognition subtest (PIAT-R) and Mathematics subtest (PIAT-M) at ages 5 and 6. Both assessments are among the most widely used for preschool and early school-aged children. The PPVT is a vocabulary test for standard American English and provides a quick estimate of verbal ability and scholastic aptitude. The PIAT-M measures attainment in mathematics. It consists of 84 multiple-choice items of increasing difficulty. It begins with such early skills as number recognition and progresses to measuring advanced concepts in geometry and trigonometry. Finally, the PIAT-R measures word recognition and pronunciation.

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

5.3. Descriptive statistics

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

6. Estimation results

6.1. Estimation results for the quasi-structural model-homogenous effects case

In this section, we present parameter estimates for the "quasistructural" model of Section 4.2. That is, we jointly estimate the

Table 5

Summary of variables used in the empirical analysis.

Variable	Mean
	(standard error)
Log (test score)	4.49855
	$(0.1861)^{a}$
Mother's education at childbirth	11.208
	(1.8972)
Mother's age at childbirth	23.136
	(4.5820)
Hispanic or black	0.8262
	(0.3790)
Birthweight (ounces)	111.97
	(21.976)
Boys (children of single mothers)	0.4976
	(0.5001)
Mother worked before giving birth	0.6431
	(0.4792)
Wage rate prior to giving birth	4.3938
	(2.0075)
Accumulated work experience prior	4.7202
to giving birth (number of years)	(6.0088)
Never married after childbirth	0.7215
	(0.4483)
Separated after childbirth	0.1540
	(0.3611)
Divorced after childbirth	0.1158
	(0.3201)
Urban	0.8189
	(0.3851)
Average yearly income (thousands)	10.9274
	(13.568)
Cumulative income (thousands)	51.1787
	(67.415)
Average childcare use (% of periods)	0.3546
	(0.3064)
Cumulative childcare use (quarters)	7.0923
	(6.1273)

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

approximate decision rules for work and childcare use, with the maternal wage and child cognitive ability production functions. Specifically, we maximize the likelihood given by approximate decision rules for work and childcare (see Eq. (12)), and the wage and test score density functions implied by Eqs. (13) and (14).

Table 6 presents the estimates of the cognitive ability production function (14) using several methods. Columns (1) and (2) present OLS and random effects (RE) estimates, respectively.

Baseline specification of the test score equation.

	(1)	(2)	(3)	(4)
	OLS	RE	IV	MLE
Cumulative childcare	0.00054	0.00013	-0.00807	-0.00698
	(0.00077)	(0.00083)	(0.00333)**	$(0.00045)^{**}$
Log (cumulative income)	-0.00263	-0.00403	0.02802	0.01919
	(0.00558)	(0.00570)	(0.02735)	(0.00218)**
Mother's education	0.01101	0.011475	0.013454	0.01298
	$(0.00266)^{**}$	$(0.00264)^{**}$	(0.00312)**	(0.00110)**
Mother's AFQT	0.00139	0.00138	0.00138	0.00132
	$(0.00022)^{**}$	(0.00026)**	(0.00034)**	$(0.00011)^{**}$
Mother's AFQT missing	0.05542	0.06422	0.06307	0.01962
	(0.01695)**	(0.02311)**	(0.01931)**	(0.01461)
Mother's age	-0.00930	-0.00465	-0.00515	-0.00356
	(0.01341)	(0.01388)	(0.01461)	(0.00555)
Mother's age squared	0.00016	0.00008	0.00006	0.00001
	(0.00027)	(0.00028)	(0.00030)	(0.00011)
I[mother's age $< 20]$	0.01100	0.01626	0.00944	0.06867
	(0.01421)	(0.01646)	(0.01532)	$(0.00661)^{**}$
I[mother's age >= 33]	0.00231	0.00860	-0.00182	0.03464
	(0.03012)	(0.02999)	(0.03250)	(0.01216)**
I[worked before]	0.01052	0.01298	0.03511	0.02844
	(0.00916)	(0.00961)	(0.01344)	(0.00376)
EXPBEF	0.00110	0.00119	0.00336	0.00314
	(0.00109)	(0.00103)	(0.00176)	(0.00040)
Gender	-0.02329	-0.02275	-0.02474	-0.01688
	(0.00685)	(0.00741)	(0.00718)	(0.00289)
Race	-0.05011	-0.05502	-0.04053	-0.04614
	(0.01012)	(0.01111)	(0.01138)	(0.00454)
Birthweight	0.00450	0.00441	0.00591	0.05762
	(0.00619)	(0.00596)	(0.00638)	(0.00225)
Number of siblings	-0.01695	-0.01748	-0.02801	-0.01590
	(0.00328)	(0.00328)	(0.00615)	(0.00135)
Child's age	0.02944	0.03262	0.03704	0.03779
	(0.00721)	(0.00616)	(0.01319)	(0.00465)
PPVTdummy	-0.25184	-0.25039	-0.25223	-0.22378
	(0.01015)	(0.00817)	(0.01032)	(0.00832)
PIAT math dummy	-0.07739	-0.07/15	-0.0/783	-0.05882
	(0.00395)	(0.00588)	(0.00398)	(0.00986)
Constant	4.58/51 (0.1573c)**	4.52602	4.433/4	4.39550
P ²	(0.15736)	(0.17190)	(0.18908)	(0.07197)
K ²	0.3745	0.0222	0.3717	0.0207
NISE _{ML}	0.0304	0.0333	0.0305	0.0297
Fraction due to permanent	-	0.3352		0.2272

(1) Ordinarly least squares. Robust standard errors (Huber–White) by child clusters. (2) Random effects. (3) Instruments are policy variables and local demand conditions listed in Table 1. Assumes welfare, rules and demand conditions have same effect in all years. Robust standard errors (Huber–White) by child clusters. (4) Full quasi-structural model.

Significant at 10%.

^{**} Significant at 5%.

Column (3) presents linear IV estimates, with the welfare and childcare subsidy rules and local demand condition variables in Table 1 used as instruments.⁴⁴ Finally, column (4) presents ML estimates from a special case of our "quasi-structural" model, where we assume the effects of childcare and income on child outcomes are homogenous across types of children and mothers.

The OLS results imply that the use of childcare has no significant effect (either statistically or quantitatively) on children's achievement, and the RE estimates are similar. However, the IV estimates imply that OLS and RE estimates are severely upward biased. The linear IV estimate implies that one-quarter of full-time work and childcare use reduces a child's test scores by 0.81%. This translates into -3.2% for each year of childcare. The ML estimates of the

quasi-structural model imply a similar result: an additional quarter of childcare reduces a child's test scores by about 0.70%. This implies that one year of full-time maternal work and childcare use reduces test scores by roughly 2.8%. That is, (0.0279/0.186) = 0.15 standard deviations of the score distribution. Using the results in Bernal and Keane (2008), this implies an effect on completed schooling of roughly 0.053–0.07 years (or about a 7.5% decrease in college completion).

It is interesting that the linear IV and quasi-structural estimates are so similar. The IV estimates rely on welfare and childcare subsidy rules and local demand conditions as instruments. The quasistructural approach relies on the same instruments to provide exclusion restrictions, and, in addition, uses exclusion/functional form restrictions implied by the structure of the model (see Table 3 and the discussion in Section 4.2). Thus, each approach relies on somewhat different identifying assumptions—particularly regarding the exact form of the decision rules for work and childcare (which the IV approach leaves implicit). Hence, each implements a selection correction (for the problem that children placed in childcare differ from those who are not) in a somewhat different way. Thus, it is comforting the results are robust across the two approaches.

⁴⁴ As we discussed in Section 4.2, linear IV requires instruments that capture effects of welfare rules and local demand conditions from the birth of the child up through time *t* on cumulative childcare use and income. To do this, in the first stage of our 2SLS procedure, we let \hat{C}_t and \hat{I}_t depend on welfare rules and local demand conditions from the birth of the child up thought age *t*. Thus, the number of instruments grows with the age of the child. To conserve on parameters, we assume that the instruments have the same coefficients at each age. In Bernal and Keane (2008), we consider alternative assumptions (e.g., allowing effects of instruments to differ by age), and show it has little effect on the results.

Ta	bl	е	7

Test score equation with interactions.

Dep. variable: log (test score)	(1)	(2)	(3)	(4)
Cumulative childcare	-0.00698	0.02529	-0.00691	0.02499
	(0,00045)**	$(0.0134)^{*}$	(0,0007)**	$(0.0152)^{*}$
Log (cumulative income)	0.01919	0.01159	0.01700	0.01305
	(0.00218)**	(0.0862)	(0.0022)**	$(0.0024)^{**}$
Childcare $* \ln A_{\circ}$	()	-0.00686	()	-0.00679
		(0.0029)**		(0.0033)**
Childcare * (Mother's education)			-0.00120	-0.00140
,, , , , , , , , , , , , , , , , ,			(0.0002)**	$(0.0002)^{**}$
$Log(income) * ln A_{o}$		0.001703		0.00137
		(0.01845)		$(0.0004)^{**}$
Log (income) * (mother's education)		· · · ·	-0.00026	-0.00032
			(0.00096)	(0.0012)
Mother's education	0.01298	0.01297	0.01317	0.01316
	(0.00110)**	$(0.0014)^{**}$	(0.0040)**	(0.0043)**
Mother's AFQT	0.00132	0.00132	0.00131	0.00132
	(0.00011)**	$(0.0002)^{**}$	(0.0001)**	$(0.0001)^{**}$
Mother's AFQT missing	0.01962	0.01956	0.01934	0.01971
	(0.01461)	(0.01489)	(0.01479)	(0.01551)
Mother's age	-0.00356	-0.00355	-0.00333	-0.00351
	(0.00555)	(0.0058)	(0.0056)	(0.0063)
Mother's age squared	0.00001	0.00001	0.00001	0.00001
	(0.00011)	(0.0001)	(0.0001)	(0.0001)
<i>I</i> [mother's age < 20]	0.06867	0.06862	0.06880	0.06866
	(0.00661)**	$(0.00858)^{**}$	$(0.00660)^{**}$	$(0.00787)^{**}$
I[mother's age >= 33]	0.03464	0.03462	0.03468	0.03465
	(0.01216)**	(0.01335)**	(0.01230)**	$(0.01440)^{**}$
I[worked before]	0.02844	0.02841	0.02841	0.02840
	(0.00376)**	(0.00413)**	(0.00377)**	(0.00413)
EXPBEF	0.00314	0.00314	0.00314	0.00314
	$(0.00040)^{**}$	$(0.00047)^{**}$	$(0.00040)^{**}$	$(0.00047)^{**}$
Gender	-0.01688	-0.01687	-0.01687	-0.01690
	(0.00289)**	(0.0032)**	(0.0029)**	(0.0033)**
Race	-0.04614	-0.04611	-0.04629	-0.04621
	(0.00454)	(0.0056)	(0.0046)	(0.0052)
Birthweight	0.05762	0.05759	0.05745	0.05759
	(0.00225)	(0.0042)	(0.0023)**	(0.0029)**
Number of siblings	-0.01590	-0.01590	-0.01592	-0.01589
	(0.00135)	(0.0013)	(0.0013)	(0.0014)
Child's age	0.03779	0.03980	0.03965	0.03961
	(0.00465)	(0.0047)	(0.0050)	(0.0063)
Constant	4.39550	4.39550	4.39038	4.39308
	(0.07197)	(0.0792)	(0.0843)	(0.0941)
MSE _{ML}	0.0297	0.0297	0.0297	0.0297
Fraction due to permanent	0.2272	0.2268	0.2270	0.2267

Test dummies not reported. Estimates are almost identical to those in Table 6. (1) No interaction terms. (2) Includes interactions of inputs with ln A₀. (3) Includes interactions of inputs with mother's education. Education is de-meaned before interacting. (4) Includes interactions with mother's education and ln A₀. Education is de-meaned before interacting.

* Significant at 10%.

** Significant at 5%.

Cumulative household income is not statistically significant under any of the estimation methods except the quasi-structural approach. But, in all cases, the estimated effect of income since childbirth is quantitatively very small. In particular, a 1% increase in cumulative income induces a 0.019% increase in child test scores, which is (0.000192/0.1861) = 0.001 standard deviations. This effect seems especially small when compared with the estimated childcare effect. For example, if cumulative household income were to double (e.g., because the mother decides to work fulltime rather than part-time after the birth of the child), then that extra income would induce a 1.3% increase in the child's scores (or 0.0133/0.186 = .07 standard deviations). However, the negative effect of each additional half year of childcare (required when the mother shifts from part- to full-time) is 1.4%, giving 7% over 5 years. Thus, while income has a positive effect on the child's achievement, it does not nearly offset the effect of maternal separation.

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

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

One advantage of the quasi-structural approach over singleequation linear IV is that, by explicitly estimating the work and childcare decision rules, and including the mother's wage function as part of the system, we get a substantial efficiency gain. Indeed, the standard error on the childcare coefficient in the test score equation falls from 0.00333 to 0.00045, a factor of 7.4, giving us much greater confidence in the estimated effect size. As we will see in Table 12, this arises in part because the wage equation residual (i.e., the mother's unobserved skill endowment) conveys a great deal of information about the unobservable in the test score equation.

In general, the point estimates are very similar for all the variables in columns (3) and (4) of Table 6. Yet, in almost every in-

Child's skill endowment ln A₀. Descriptive statistics.

	ln A _o	Observed part of ln A _o	Unobserved part of ln A _o
Mean Minimum Maximum Standard error Variance Fraction of total variance	4.66631 4.18886 5.11929 0.11131 0.01229	4.66676 4.44012 4.93039 0.07497 0.00562 0.457445	-0.00045 -0.31972 0.34099 0.08165 0.00667 0.542555

stance, the standard errors on the quasi-structural estimates are much smaller than those on the IV estimates. Thus, by imposing some structure, we obtain an efficiency gain while getting estimates that are very close to linear IV.

6.2. Estimation results for the quasi-structural model—heterogeneous effects case

6.2.1. Estimates of the test score equation

A key advantage of the quasi-structural approach over linear IV is that we can accommodate unobserved heterogeneity in effects of inputs on child cognitive outcomes. In Table 7 through 12, we report estimates of the full model that includes interactions between initial child ability $(\ln A_0)$ and both cumulative childcare and cumulative income (as in Eq. (14)).

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

Hence, in Table 8, we report descriptive statistics about the estimated $\ln A_0$, (i.e., mean, standard deviation, minimum, maximum), which helps one to interpret the quantitative importance of the interactions. And, in Fig. 2, we plot the derivatives of log scores with respect to cumulative childcare and income, as a function of $\ln A_0$. This shows how the effects of inputs differ with $\ln A_0$.

At the mean value of the child ability endowment, the estimated effect of an additional quarter of full-time maternal work and childcare use is -0.67%, which translates into an effect of roughly -2.7% per year (about 0.14 std. dev. of the score distribution). It is interesting that this mean effect is almost identical to what we obtained in the homogenous effects model of Table 6 column (4), and similar to the effect we estimated using linear IV in Table 6 column (3).

Fig. 2 also shows that the effect of childcare ranges from -0.52% per quarter (-2.1% per year) for a child with an ability endowment two standard deviations below average to -0.83% per quarter (-3.3% per year) for a child with an endowment two standard deviations above average. In contrast, the interaction of income with $\ln A_0$ is statistically and quantitatively insignificant.

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



Fig. 2. (a) Effect of childcare use on cognitive ability $d \ln St/dC_t = 0.02529 - 0.00686 \ln A_0$. (b) Effect of log (cumulative income) on cognitive ability $d \ln St/d \ln I_t = 0.01159 + 0.001703 \ln A_0$.

 Table 9

 Parameter estimates of the wage equation.

	Variable	Parameter	Std. error
Initial wage ed	quation		
β_{96}	Intercept	0.285278	(0.046167)
β_{97}	Education	0.040127	(0.008805)
β_{98}	Age	0.014890	(0.003761)
β_{99}	Age ²	0.000075	(0.000075)
β_{100}	Race	0.187024	(0.021989)
β_{101}	AFQT	0.004514	(0.191204)
Re-employme	ent wage equation		
$\beta_{102.1}$	UE	-0.000386	(0.000056)
$\beta_{102,2}$	SWAGE	0.006473	(0.001938)
$\beta_{102,3}$	SERV	0.051242	(0.018417)
β_{103}	t	-0.002976	(0.000206)
β_{104}	Et	0.009913	(0.001083)
β_{105}	f_{t-1}	0.053151	(0.008841)
β_{106}	p_{t-1}	0.034901	(0.009376)
β_{107}	$E_t * educ$	0.000052	(0.001160)

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

We de-mean education prior to interacting it with cumulative childcare. Hence, in column (3), the linear childcare term is interpretable as the effect of childcare on child outcomes for a mother with average education (11.2 years). The estimate is -0.69% per quarter, or -2.8% per year. The interaction term is -0.12% per quarter (or -0.48% per year), implying that, for a mother with only 9.2 years of education, the negative effect of childcare is -2.8

Table 10
Parameter estimates of the work probit

	Variable	Parameter	Std. error
β ₀₁	Intercept	-17.38835	(0.035315)
β ₁	age	0.236930	(0.001779)
β ₂	age ²	-0.006417	(0.000039)
β3	education	0.308073	(0.001470)
β ₄	race	0.442155	(0.005374)
β ₅	\mathbf{f}_{t-1}	1.957106	(0.021490)
β ₈	AFQT	0.322740	(0.000627)
β ₁₁₀	Et	0.060500	(0.002499)
β ₁₀	t	0.070124	(0.000675)
β ₈₉	UE	0.003781	(0.006883)
β ₉₀	SWAGE20	0.273700	(0.084972)
β ₉₁	SERV	2.197499	(0.028775)
β ₁₁	BW	-0.117509	(0.002067)
β ₁₂	gender	-0.609491	(0.003625)
β ₁₂₁	NSIB _t	0.000356	(0.002802)
β ₁₃	I[age<20]	0.006230	(0.005847)
β ₇₁	I[age>33]	-0.552271	(0.013812)
β ₁₀₁	EXPBEF	0.000054	(0.005659)
β ₁₁₃	workbef	0.004854	(0.014623)
β ₇	Ct	-0.141464	(0.002576)
β ₁₅	$I[C_t>0]$	-0.009982	(0.025851)
β ₁₆	I[t=1]	0.000175	(0.024201)
β ₁₇	I[t<5]	-0.000027	(0.012282)
β ₉₈	I ^c _{t-1}	-0.035636	(0.068155)
β ₁₈₁	BEN	0.000096	(0.000026)
β ₉	D_{t}	0.043932	(0.000789)
β ₁₈₂	I[TLI or DWR]	0.252651	(0.139407)
β ₁₈₃	TL LENGTH	-0.176754	(0.010957)
β ₁₈₅	I[TL HIT or WR HIT]	2.015537	(0.235916)
β ₁₈₆	REMAIN TL ELIG	0.354263	(0.017052)
β ₁₈₈	REMAIN CAT ELIG	0.001409	(0.000091)
β ₁₈₁₁	WR LENGTH	-0.016405	(0.009260)
β ₁₈₁₃	AGE EXEM	0.000995	(0.001694)
β ₁₈₁₄	EXEMP	-0.885236	(0.066734)
β ₁₈₁₈	FLAT_DIS	0.061179	(0.000490)
β ₁₈₁₉	PERC DIS	0.128807	(0.002960)
β ₁₈₂₁	ENFORCE	0.117756	(0.004298)
β ₁₈₂₂	EITC	-0.070353	(0.007620)
β19	CCDF	-0.175724	(0.004420)

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

(2)(-0.48) = -1.8% per year. Thus, the adverse effect of childcare use is much smaller for less educated mothers.

Bernal and Keane (2008) obtain very similar point estimates using linear IV, i.e., a linear childcare effect of -0.0062 and an interaction with mother's education of -0.00174. But the interaction has a standard error of 0.0010 and, hence, is only significant at the 10% level.⁴⁵ Thus, the increased efficiency of the quasi-structural approach (which reduces the standard error by a factor of roughly

Part-time Probit						
	Variable	Parameter	Std. error			
β ₀₂	Intercept	-7.861538	(0.118154)			
β_{116}	age	0.117989	(0.007260)			
β_{117}	age ²	-0.003215	(0.000170)			
β_{20}	education	0.337879	(0.006281)			
β_{21}	race	0.230337	(0.029273)			
β_6	p _{t-1}	1.771106	(0.044958)			
β_{23}	AFQT	-0.080644	(0.001411)			
β_{111}	Et	0.054194	(0.007824)			
β ₈₈	t	0.005698	(0.021040)			
β_{92}	UE	0.001896	(0.019339)			
β_{93}	SWAGE20	-0.735904	(0.019979)			
β_{94}	SERV	1.384997	(0.067386)			
β_{25}	BW	0.512115	(0.016102)			
β_{26}	gender	0.257402	(0.022183)			
β_{122}	NSIB _t	-0.001015	(0.013024)			
β_{27}	I[age<20]	0.800193	(0.036788)			
β ₇₂	I[age>33]	-6.738273	(0.057939)			
β_{102}	EXPBEF	0.000675	(0.002068)			
β_{114}	workbef	0.002678	(0.070693)			
β_{22}	C _t	-0.072690	(0.007202)			
β ₂₉	$I[C_t > 0]$	0.498643	(0.082364)			
β_{30}	I[t=1]	-1.251982	(0.019873)			
β_{31}	I[t<5]	0.002028	(0.056250)			
β_{99}	I ^c _{t-1}	-0.354102	(0.006412)			
β_{321}	BEN	0.002941	(0.000119)			
β_{24}	D _t	-0.036316	(0.003505)			
β_{322}	I[TLI or DWR]	1.181734	(0.232954)			
β_{323}	TL_LENGTH	-0.063936	(0.006909)			
β_{325}	I[TL_HIT or WR_HIT]	2.310756	(0.282968)			
β_{326}	REMAIN_TL_ELIG	0.193959	(0.012152)			
β_{328}	REMAIN_CAT_ELIG	-0.016354	(0.000540)			
β_{3211}	WR_LENGTH	-0.371060	(0.011398)			
β_{3213}	AGE_EXEM	0.002444	(0.002373)			
β_{3214}	EXEMP	0.089808	(0.076026)			
β_{3218}	FLAT_DIS	0.169071	(0.000644)			
β_{3219}	PERC_DIS	0.339384	(0.010223)			
β_{3221}	ENFORCE	0.662682	(0.022656)			
β_{3222}	EITC	0.194178	(0.018562)			
β_{33}	CCDF	-0.111043	(0.023759)			

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

3.5) is important for obtaining the clear conclusion the childcare has a less adverse effect for less educated mothers.

6.2.2. Estimates of the work, childcare and wage equations

We next discuss the estimates of the other three equations of the quasi-structural system. Table 9 presents the estimates of the initial and re-employment wage equation. All parameters have expected signs and reasonable magnitudes. For example, an additional year of education is associated with 4% increase in initial wages. Similarly, the age and age² coefficients imply that, at age 20, an additional year of potential experience (i.e., age) is

 $^{^{\}rm 45}$ Nevertheless, Bernal and Keane (2008) find that if a mother's education is 4 years above the sample average, the negative childcare effect increases from -0.62% to -1.31%. The later estimate has a standard error of 0.41, obtained by the delta method, and hence a *t*-stat of -3.19.

Table	11
-------	----

Parameter estimates of the childcare probit.

	Variable	Parameter	Std. error
β_{50}	Intercept	-2.744015	(0.263171)
β_{51}	Age	0.429771	(0.017690)
β ₅₂	Age ²	-0.009583	(0.000357)
β_{53}	Education	0.062875	(0.003044)
β_{54}	Race	0.062124	(0.013632)
β_{55}	AFQT	0.005769	(0.000331)
β_{56}	f_{t-1}	-0.213544	(0.064352)
β_{57}	p_{t-1}	-0.460165	(0.037726)
β_{58}	Et	0.007387	(0.008834)
β_{59}	t	-0.003138	(0.000489)
$\beta_{60,1}$	UE	-0.003047	(0.003940)
$\beta_{60,2}$	SWAGE20	-0.072581	(0.004545)
$\beta_{60,3}$	SERV	-0.276849	(0.016542)
β_{61}	BW	0.076096	(0.007453)
β_{62}	Gender	-0.028140	(0.008817)
β_{63}	<i>I</i> [age < 20]	0.411772	(0.020519)
β_{64}	<i>I</i> [age> 33]	0.797243	(0.176605)
β_{65}	EXPBEF	0.001653	(0.001446)
β_{66}	workbef	0.004992	(0.016028)
β_{67}	Ct	0.001756	(0.008590)
β_{68}	NSIB _t	-0.000440	(0.004964)
β_{69}	Dt	-0.011042	(0.001537)
β_{70}	$I[C_t > 0]$	0.098599	(0.019532)
β_{71}	I[t = 1]	0.003646	(0.066120)
β_{72}	I[t < 5]	-0.031828	(0.034687)
β_{73}	I_{t-1}^c	1.177289	(0.031967)
$\beta_{74,1}$	BEN	-0.001414	(0.000047)
$\beta_{74,2}$	I[TLI or DWR]	0.213688	(0.162023)
$\beta_{74,3}$	TL_LENGTH	0.010261	(0.012367)
$\beta_{74,4}$	I[TL_HIT or WR_HIT]	0.556541	(0.166595)
$\beta_{74,5}$	REMAIN_TL_ELIG	-0.016976	(0.014242)
$\beta_{74,6}$	REMAIN_CAT_ELIG	-0.013165	(0.000677)
$\beta_{74,7}$	WR_LENGTH	0.030722	(0.008422)
$\beta_{74,8}$	AGE_EXEM	-0.004698	(0.002427)
$\beta_{74,9}$	EXEMP	-0.170118	(0.070378)
$\beta_{74,10}$	FLAT_DIS	-0.000302	(0.000419)
$\beta_{74,11}$	PERC_DIS	-0.023839	(0.006180)
$\beta_{74,12}$	ENFORCE	0.126986	(0.010611)
$\beta_{74,13}$	EITC	0.209939	(0.022456)
β_{75}	CCDF	-0.073595	(0.014738)

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

associated with a 4.5% increase in the initial wage.⁴⁶ The local demand conditions are highly significant with expected signs.

Tables 10 and 11 present the estimates of the work and childcare probits. The estimated effects of welfare rules are generally reasonable. If a State has a time limit or work requirement, it increases the probability of work (especially parttime) and of childcare use (although the latter effect is only marginally significant). The indicator for whether a woman might be subject to a time limit or work requirement, I[TL_HIT or WR_HIT] has large and highly significant positive coefficients in the value functions for both full- and part-time work and childcare utilization.⁴⁷ A longer benefit receipt time limit significantly reduces the probability a mother works, although the effect on childcare is insignificant. A longer work requirement time limit significantly reduces the probability that a mother works part-time. The number of work requirement exemptions (a measure of strictness of State welfare policy) has a large and highly significant negative effect on the probability a mother works full-time, and lowers the probability of using childcare. As expected, both the flat and percentage earnings disregards increase the probability of work.

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

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

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

Among the most interesting parameters are the error correlations, reported in Table 12, as these implement the selection correction for types of children placed in childcare. The correlation between permanent unobservables in the test score and mother's wage equation is -0.69, implying, somewhat surprisingly, that mothers with high unobserved skill endowments tend to have children with relatively low unobserved ability endowments.⁴⁸ On the other hand, the permanent unobservables in the full- and parttime work equations are positively correlated with the child's unobserved ability endowment. Thus, as expected, working mothers tend to have relatively high-skilled children, biasing OLS estimates of work/childcare effects in a positive direction. The permanent error component in the childcare equation is very small, so it has little effect.

6.3. Model fit

Fig. 3 shows the fit of the quasi-structural model to the choice frequencies in Fig. 1, based on 15,000 simulated individuals. The model fits the choice data quite well, particularly for the most common alternatives, i.e., stay at home/do not use childcare and work/use childcare. Chi-squared goodness-of-fit test statistics shown in Table 13 confirm the graphical results. The only mild rejections are in the 9th and 11th quarters after childbirth— at those ages, the model slightly understates the percent using childcare but not working.

The model also provides a good fit to wages by mother characteristics and test scores by child age (see Fig. 4 and Table 14).

 $^{^{\}rm 46}$ The standard errors on age and ${\rm age}^2$ are very large because they are highly collinear due to the young age and fairly limited age range of the sample. But they are jointly significant.

⁴⁷ Due to collinearity between indicators for whether a State had a time limit and whether it had a work requirement (i.e., if a State has one, it almost always has the other), we were forced to combine the variables TLI and DWR into a single indicator for whether a State had either a work requirement or a time limit. A similar problem forced us to combine indicators for whether a woman could have been hit by a binding time limit or work requirement, TL_HIT and WR_HIT, into a single indicator for whether she could have been hit by either a time limit or work requirement.

 $^{^{48}}$ This is less surprising given that the mother's observed skill endowment controls for her education and AFQT.

Estimated error covariance and correlation matrices.

Variance covariance estimates of the vector of error terms			Correlation matrix of the vector of error terms								
	ε_{f}	ε_p	ε _c	\mathcal{E}_{S}	ε_w		\mathcal{E}_{f}	ε_p	ε _c	\mathcal{E}_{S}	ε_w
\mathcal{E}_{f} \mathcal{E}_{p} \mathcal{E}_{c} \mathcal{E}_{s} \mathcal{E}_{w}	1.0000000 -0.5334026 0.0130520 0.0176224 0.0007788	6.7770369 -0.0878713 0.0530314 -0.0179218	1.0000000 0.0023566 0.0002907	0.0296734 —0.0169229	0.1721507	\mathcal{E}_f \mathcal{E}_p \mathcal{E}_c \mathcal{E}_s \mathcal{E}_w	1.0000000 -0.2048968 0.0130520 0.1023011 0.0018770	1.0000000 -0.0337542 0.1182578 -0.0165924	1.0000000 -0.0136804 0.0007007	1.0000000 -0.2367748	1.0000000
Covariance matrix of the permanent components μ_k				Corre	elation matrix of	the permanent	components μ_k				
	μ_f	μ_p	μ_{c}	μ_s	μ_w		μ_f	μ_p	μ_c	μ_s	μ_w
$ \begin{array}{c} \mu_f \\ \mu_p \\ \mu_c \\ \mu_s \\ \mu_w \end{array} $ Cova	0.8171407 0.5334026 0.0130520 0.0176224 0.0007788 riance matrix of	2.0039500 -0.0878713 0.0530314 -0.0179218	0.0041639 -0.0023566 0.0002907	0.0067301 —0.0169229	0.0884818	μ_f μ_p μ_c μ_s μ_w	$\begin{array}{c} 1.0000000\\ -0.4168341\\ 0.2237566\\ 0.2376328\\ 0.0028962 \end{array}$	1.0000000 0.9619470 0.4566470 0.0425610	1.0000000 0.4451643 0.0151472	1.0000000 —0.6934854	1.0000000
	v_f	v _p	vc	vs	v_w						
v_f v_p v_c v_s v_w	0.1828593 0.0000000 0.0000000 0.0000000 0.0000000	4.7730869 0.0000000 0.0000000 0.0000000	0.9958361 0.0000000 0.0000000	0.0229434 0.0000000	0.0836689						

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





6.4. Robustness checks

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

Table 1	3
---------	---

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

* Statistically significant at 0.05 (critical value = 7.82).

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

We address this issue in columns (3)–(4). In (3), we remove the age controls entirely.⁵⁰ This has almost no impact on the estimated childcare effect. At the mean of $\ln A_0$, the estimated effect is -0.66% per quarter. In column (4), we restrict the sample to mothers who were at least 24 years old at the time of childbirth. This also has little impact on the estimated childcare effect, which is -0.61% at the mean of the data. There is no doubt that the welfare rules are

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

Та	ble	14
	_	

Fit	to	test	scores	and	initial	wages
LUL I	ιυ	lest	scores	anu	IIIIIIdi	wages.



Fig. 4. (a) Average log (hourly wage) in the sample. (b) Average log (hourly wages) by education category.

highly correlated with mother's age at birth, so we take the insensitivity of results to controls for age as evidence that mother's age is not, *ceteris paribus*, quantitatively important for child outcomes.

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

⁵¹ This result contradicts the National Research Council and Institutes of Medicine (2000), who conclude that there is compelling evidence that maternal employment in the first year can have a negative effect on infant development. Our reading of the prior evidence is rather different. First, most of the studies they cite fail to control

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

	Actual	Predicted	
Total average	1.3760	1.3662	
<high school<br="">>High school</high>	1.3142 1.5782	1.3245 1.5707	
30+ years old	1.5649	1.6023	
< 30 years old	1.3462	1.3440	
White	1.2622	1.2694	

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

Test score equation. Robustness checks: Children's ages, mother's age and age-specific effects.

Dep. variable: log (test score)	(1)	(2)	(3)	(4)	(5)	(6)
Cumulative childcare	0.02529 (0.0134) ^{**}	0.02860 (0.0103) ^{**}	0.02778 (0.0109) ^{**}	0.03046 (0.0126)**		0.03451 (0.0125) ^{**}
Cumulative childcare 1st year					0.10170	
					$(0.0479)^{**}$	
Cumulative childcare after 1st year					0.04080	
					(0.0129)**	
Log (cumulative income)	0.01159	0.00111	0.00352	0.02144	0.01148	0.01471
Total childcare $* \ln A_o$	(0.0862) -0.00686 $(0.0029)^{**}$	(0.0626) -0.00758 $(0.0022)^{**}$	(0.0675) -0.00729 (0.0023)**	(0.0932) -0.00781 $(0.0027)^{**}$	(0.0607)	(0.0867) -0.00899 $(0.0027)^{**}$
Childcare 1st year $* \ln A_0$	(0.0023)	(0.0022)	(0.0023)	(0.0027)	-0.02034	(0.0027)
,					(0.0101)**	
Childcare after 1st year * In A					-0.01062	
					(0.0027)**	
$Log(income) * ln A_{a}$	0.001703	0.00609	0.00469	0.00623	0.005937	0.000998
	(0.01845)	(0.0133)	(0.0143)	(0.0200)	(0.01290)	(0.01854)
Mother's education	0.01297	0.01285	0.01287 0	.0128018	0.01295	0.01339
Mother's AFQT	0.0014)	0.0011)	0.00129	0.00126	0.0011)	0.00131
Mathen's AFOT missing	(0.0002)**	(0.0001)	(0.0001)**	(0.0002)**	(0.0001)**	(0.0002)
Mother's APQ1 missing	(0.01489)	(0.01044)	(0.01311)	(0.0272)	(0.0104)	(0.02073)
Mother's age	-0.00355	-0.00049	()	-0.00204	-0.00125	-0.00122
	(0.0058)	(0.0083)		(0.0128)	(0.0441)	(0.0063)
Mother's age squared	0.00001	-0.00003		-0.00002	-0.00003	-0.00003
	(0.0001)	(0.0238)		(0.0002)	(0.0072)	(0.0001)
I[mother's age < 20]	0.06862	0.06950			0.06853	0.07240
	(0.00858)**	(0.00648)**			(0.0064)**	$(0.0088)^{**}$
I[mother's age \geq 33]	0.03462	0.03562		0.03535	0.03461	0.03616
	(0.01335)**	(0.01013)**		(0.0125)**	(0.01056)**	(0.01342)**
I[worked before]	0.02841	0.02807	0.02823	0.02795	0.02074	0.02902
EVDREE	(0.00413) ^{**}	(0.00326)**	(0.00369) ^{**} 0.00317	(0.0056)**	(0.00318)**	(0.00442)**
EAT DEF	$(0.00047)^{**}$	$(0.00037)^{**}$	(0.00033)**	(0.0004)**	(0.00038)**	$(0.00046)^{**}$
Gender	-0.01687	-0.01662	-0.01651	-0.01659	-0.01672	-0.01664
Paca	$(0.0032)^{**}$	(0.0025)**	(0.0028)**	(0.0036)**	(0.0024)**	$(0.0033)^{**}$
Nate	$(0.0056)^{**}$	(0.0043)**	$(0.0047)^{**}$	$(0.0065)^{**}$	$(0.0042)^{**}$	$(0.0057)^{**}$
Birthweight	0.05759	0.05621	0.05673	0.05614	0.05724	0.05820
Number of ciblings	(0.0042)**	(0.0031)**	(0.0034)**	(0.0046)**	(0.0032)**	$(0.0042)^{**}$
Number of sidnings	(0.0013)**		(0.001397)	$(0.0013)^{**}$	$(0.0010)^{**}$	$(0.0013)^{**}$
Number of siblings 0–5 years of age	(0.0010)	-0.02033	(0.0011)	(0.0010)	(0.0010)	(0.0013)
		(0.0015)**				
Number of siblings 6–17 years of age		-0.00667				
		(0.0012)**				
Child's age	0.03980	0.03937	0.03644	0.03973	0.03958	0.04000
	$(0.0047)^{**}$	$(0.0042)^{**}$	$(0.0044)^{**}$	$(0.0062)^{**}$	$(0.0043)^{**}$	$(0.0047)^{**}$
Constant	4.39550	4.37606	4.37106	4.40033	4.38648	4.36419
MSE _{MI}	0.0297	0.0294	0.0294	0.0296	0.0295	0.0296
Fraction due to permanent	0.2268	0.2237	0.2231	0.2286	0.2256	0.2321
Number of observations	3787	3787	3787	1680	3787	3787

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

** Significant at 5%.

for the fact that women who work in the first year after childbirth are systematically different from women who do not. Second, the results of the prior literature are not really so consistent. Of particular note is Waldfogel et al. (2002), the only study in the area that uses sibling fixed effects in an attempt to correct for endogeneity of maternal employment. They follow a sample of children of the NLSY up to ages 7

and 8. Their OLS estimates imply a negative effect of maternal employment in the first year on PPVT and PIAT scores, but their FE estimates show no negative effects. Thus, we do not view our failure to find a negative first year effect as inconsistent with prior literature.

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

As we noted in Section 4, there are advantages and disadvantages to each of the quasi-structural, fully structural and singleequation IV approaches. An advantage of IV is that one can estimate models quickly, so robustness to many alternative specifications can be checked. This is difficult in quasi-structural/fully structural approaches, as estimation is so time consuming.

Our companion article Bernal and Keane (2008) adopts a linear IV approach, and examines a more extensive range of specifications for the cognitive ability production than we examine here. There, we find that an estimated "average" childcare effect of roughly -0.73% per quarter is remarkably robust to changes in the specification in the production function, as well as to the instruments used in the estimation. We also find, consistent with results here, that the negative effect of childcare is more pronounced when the child has a higher ability endowment and/or the mother is more educated. We also look at childcare quality, and find that high quality childcare (i.e., formal center-based care) does not have any detrimental effects on children.⁵² It is only informal care (i.e., noncenter based care provided by relatives or non-relatives) that has a negative effect.

7. Conclusions

This article evaluates the effects of maternal work and childcare use on child cognitive development, using the sample of single mothers in the NLSY. In particular, we assess the effects of maternal vs. alternative care provider time inputs, and household income, on child cognitive test scores recorded at ages 3, 4, 5 and 6. To deal with the potential bias created by unobserved heterogeneity of mothers and children, and systematic selection of certain types of children into childcare, we develop a model of mothers' employment and childcare decisions. Closely guided by this model, we obtain approximate decisions rules for employment and childcare use, and estimate these jointly with the child's cognitive ability production function—what we term a "quasistructural" approach. This joint estimation implements a dynamic selection correction.

To help identify our dynamic selection model, we take advantage of plausibly exogenous variation in employment/childcare use created by variation in welfare rules and local demand conditions across States and over time—especially the large changes created



Fig. 5. Age-specific effect of childcare use on cognitive ability.

by the 1996 welfare reform and earlier welfare waivers. These variables provide natural exclusion restrictions, as it is plausible they enter decision rules for employment and childcare use, while not entering the child cognitive ability production function. These instruments are also quite powerful, in that they explain a substantial part of the variation in work and childcare use by single mothers.

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

The other advantage of the quasi-structural approach is that it easily accommodates unobserved heterogeneity in the effect of interest. We do find substantial heterogeneity. The effect of childcare on test scores ranges from -2.1% per year for a child with an ability endowment two standard deviations below the average

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

⁵³ In a simplified version of our quasi-structural model that assumes homogeneous effects of childcare, the coefficient on full-time quarterly work/childcare use in the log test score equation is -0.00698 with a standard error of 0.00045(t = -15.4). Using linear IV, the coefficient is -0.00807 with a standard error of 0.00333(t=-2.42).

Table A.1

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

Dependentvariable \rightarrow Pr(usingchildcareint)	
Whether worked before giving birth	0.592015
	(0.2078) ^b
(Whether worked before) \times (Avg. wage before)	-0.06419
	$(0.0398)^{a}$
Total work experience (prior to giving birth)	-0.005986
	(0.0194)
Child's race	-0.08744
	(0.1702)
Child's gender	0.049666
	(0.1196)
Mother's education	0.082132
	(0.0384) ^b
Total work experience since child birth	-0.398349
	$(0.0698)^{b}$
Total childcare use since child birth	0.222627
	(0.0527) [₽]
Whether used childcare or not in $t - 1$	1.780094
	(0.1639) ^b
Estimation	Probit
Number of observations	867
Pseudo- <i>R</i> ²	0.4585

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

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

to -3.3% per year for a child with an ability endowment two standard deviations above the average. Observed heterogeneity is important as well. For example, for a mother with average education (11.2 years) the effect of a year of childcare is -2.8%, while for a mother with only 9.2 years of education, the negative effect of a year of childcare use is only -2.8 + (2)(-0.48) = -1.8%.

We also find that the effect of household income since childbirth is quantitatively small. In particular, a 100% increase in the cumulative household income is associated with an increase of roughly 1.3% in the test scores. However, the negative effect of each additional half year of childcare (required for the mother to double work hours) is 1.4%, giving 7% over 5 years. Thus, while income has a positive effect on a child's achievement, it does not nearly offset the effect of maternal separation. One should be careful not to conclude from this that income is unimportant. Since we control for maternal education and AFQT, this result is consistent

Table B.1

Cognitive ability tests in our NLSY sample.

with a view that the permanent income is significant in determining the parental investment in children and, hence, the children's achievement, while transitory fluctuations in income are much less relevant.⁵⁴

Our study of the case of single mothers extends earlier work by Bernal (2008), 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 childcare results in a 1.8% reduction in child cognitive ability test scores. A key motivation of our work is to see if that result generalizes from married to single mothers. Our estimate for single mothers is larger (2.7%), but the similarity of the results is fairly striking. Bernal (2008) also found heterogeneity in childcare effects (with child ability endowments) similar to what we find here.

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

In interpreting our results, it is important to remember that we do not incorporate choice of type/quality of childcare in our model. So we are basically estimating the effect of the average type of childcare that single mothers use. Including choice of quality in a structural or quasi-structural framework is difficult, because it greatly expands the choice set, but it is fairly easy in a linear IV setting—provided the instruments help predict quality choice. In our companion, article Bernal and Keane (2008), which adopts a linear IV approach, we find that the type of childcare is very important. Most single mothers use informal options that are of relatively low quality and have significant negative effects on children. But high quality center-based care does not have adverse effects.

Finally, an important caveat, noted in Section 4, is that our model assumes childcare use reduces the maternal time input

⁵⁴ The finding of small effects of income is reminiscent of findings in Blau (1999b), that household income has small effects on outcomes for young children after controlling for family background characteristics like parental education. It is also reminiscent of findings in Cameron and Heckman (1998) to the effect that permanent income largely determines parental investments in children, with transitory income fluctuations playing a minor role (although their results are for school age rather than pre-school children).

PPVT		PIAT-Math		PIAT-reading	PIAT-reading	
3	4	5	5	6	5	6
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)
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)
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)
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)
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)
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)
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 3 80.263 (14.952) 78.007 (14.169) 92.167 (13.348) 82.820 (14.369) 76.301 (15.025) 79.753 (14.664) 80.707 (15.225)	PPVT 3 4 80.263 74.334 (14.952) (19.512) 78.007 70.836 (14.169) (17.958) 92.167 89.299 (13.348) (18.885) 82.820 78.748 (14.369) (18.917) 76.301 68.748 (15.025) (18.847) 79.753 72.242 (14.664) (20.048) 80.707 76.299 (15.225) (18.820)	PPVT 3 4 5 80.263 74.334 83.767 (14.952) (19.512) (17.504) 78.007 70.836 82.135 (14.169) (17.958) (16.889) 92.167 89.299 93.852 (13.348) (18.885) (18.001) 82.820 78.748 88.743 (14.369) (18.917) (17.648) 76.301 68.748 79.508 (15.025) (18.847) (16.245) 79.753 72.242 83.035 (14.664) (20.048) (18.143) 80.707 76.299 84.569 (15.225) (18.820) (16.783)	PPVT PIAT-Math 3 4 5 5 80.263 74.334 83.767 94.719 (14.952) (19.512) (17.504) (14.329) 78.007 70.836 82.135 93.836 (14.169) (17.958) (16.889) (14.289) 92.167 89.299 93.852 99.576 (13.348) (18.855) (18.001) (13.634) 82.820 78.748 88.743 97.084 (14.369) (18.917) (17.648) (14.178) 76.301 68.748 79.508 91.767 (15.025) (18.847) (16.245) (13.991) 79.753 72.242 83.035 93.726 (14.664) (20.048) (18.143) (14.307) 80.707 76.299 84.569 95.739 (15.225) (18.820) (16.783) (14.305)	$\begin{array}{c c c c c c c c c c c c c c c c c c c $	$ \begin{array}{ c c c c c c c c c c c c c c c c c c c$

PPVT: Peabody picture vocabulary test. PIAT: Peabody individual achievement test.

Table C.1

Average test scores for children born prior to 1990 by State characteristics.

	Average	St. Dev	t test
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. State of residence at the time of test (i.e., age 3, 4 or 5).

one-for-one. This is unavoidable, as we lack data on maternal "quality" contact time with the child. Thus, our estimated childcare effect may not capture the pure effect of substituting childcare for maternal time; it may also capture adjustments to quality time and goods inputs that mothers make simultaneously with placing children in childcare.

Acknowledgements

We acknowledge support from the Australian Research Council grants FF0561843 and DP0774247 as well as several grants from the Minnesota Supercomputing Institute. We wish to acknowledge helpful comments from Robert Moffitt, Kenneth Wolpin, and other participants to the Conference on "Structural Models in Labor Aging and Health"- UNC and Duke (2005) and one anonymous referee.

Appendix A

See Table A.1.

Appendix B

See Table B.1.

Appendix C

See Table C.1.

References

- Baydar, N., Brooks-Gunn, J., 1991. Effects of maternal employment and childcare arrangements on preschoolers' cognitive and behavioral outcomes: Evidence from children of the national longitudinal survey of youth. Developmental Psychology 27 (6), 932–945.
- Bernal, R., 2008. The effect of maternal employment and childcare on children's cognitive development. International Economic Review 49 (4), 1173–1209.
- Bernal, R., Keane, M.P., 2008. Childcare choices and children's cognitive achievement: The case of single mothers. Working Paper. Universidad de los Andes, UTS and Arizona State University.
- Blau, D., 1999. The effects of childcare characteristics on child development. The Journal of Human Resources XXXIV (4).
- Blau, D., 1999b. The effect of income on child development. Review of Economics and Statistics 81 (2), 261–276.
- Blau, F., Grossberg, A., 1992. Maternal labor supply and children's cognitive development. The Review of Economics and Statistics 74 (3), 474–481.
- Burchinal, M.R., Ramey, S., Reid, M., Jaccard, J., 1995. Early childcare experiences and their association with family and child characteristics during middle childhood. Early Childhood Research Quarterly 10, 33–61.
- Cameron, S.V., Heckman, J.J., 1998. Life cycle schooling and dynamic selection bias: Models and evidence for five cohorts of American males. Journal of Political Economy 106 (2).
- Caughy, M., DiPietro, J., Strobino, D., 1994. Daycare participation as a protective factor in the cognitive development of low-income children. Child Development 65, 457–471.
- Chase-Lansdale, P.L., Moffitt, R., Lohman, B., Cherlin, A., Coley, R., Pittman, L., Roff, J., Votruba, E., 2003. Mothers' transitions from welfare to work and the well-being of preschoolers and adolescents. Science 299 (March), 1548–1552.

- Cunha, F., Heckman, J., Lochner, L., Masterov, D., 2006. Interpreting the evidence on life cycle skill formation. In: Hanushek, E., Welch, F. (Eds.), Handbook of the Economics of Education. North-Holland, Amsterdam, pp. 697–812.
- Duncan, G., NICHD Early ChildCare Research Network, 2003. Modeling the impacts of childcare quality on children's preschool cognitive development. Working paper, Northwestern University.
- Fang, H., Keane, M., 2004. Assessing the impact of welfare reform on single mothers. Brookings Papers on Economic Activity 1.
- Geronimus, A., Korenman, S., Hillemeier, M., 1994. Does young maternal age adversely affect child development? Evidence from cousing comparisons in the united states. Population and Development Review 20, 585–609.
- Han, W., Waldfogel, J., Brooks-Gunn, J., 2001. The effects of early maternal employment on later cognitive and behavioral outcomes. Journal of Marriage and the Family 63 (2), 336–354.
- Haveman, R., Wolfe, B., 1994. Succeding Generations: On the Effects of Investments in Children. Russell Sage Foundation, New York.
- James-Burdumy, S., 2005. The effect of maternal labor force participation on child development. Journal of Labor Economics 23 (1), 177–211.
- Keane, M., 1992. A note on identification in the multinomial probit model. Journal of Business and Economic Statistics 10 (2), 193–200.
- Keane, M., 1994. A computationally practical simulation estimator for panel data. Econometrica 62 (1), 95–116.
- Keane, M., Moffitt, R., 1998. A structural model of multiple welfare program participation and labor supply. International Economic Review 39 (3), 553–589.
- Keane, M., Wolpin, K., 1997. The career decisions of young men. Journal of Political Economy 105 (3), 473–522.
- Keane, M., Wolpin, K., 2001. The effect of parental transfers and borrowing constraints on education attainment. International Economic Review 42 (4), 1051–1103.
- Keane, M., Wolpin, K., 2002a. Estimating welfare effects consistent with forwardlooking behavior. Part I: Lessons from a simulation exercise. Journal of Human Resources 37 (3), 570–599.
- Keane, M., Wolpin, K., 2002b. Estimating welfare effects consistent with forwardlooking behavior. Part I: Empirical results. Journal of Human Resources 37 (3), 600–622.
- Keane, M., Wolpin, K., 2006. The role of labor and marriage markets, Preference heterogeneity and the welfare system in the life cycle decisions of black, Hispanic and White Women. Working Paper, University of Pennsylvania.
- Lamb, M., 1996. Effects of nonparental childcare on child development: An update. The Canadian Journal of Psychiatry 41, 330–342.
- Lopez, R., 2003. Are children of young mothers disadvantaged because of their mother's age or family background?. Child Development 74, 465–474.
- Love, J.M., Schochet, P., Meckstroth, A., 1996. Are they in real danger? What research does -and does not- tell us about childcare quality and children's well-being. Mathematica Policy Research (ERIC Document Reproduction Service No. ED145 030), Plainsboro, NJ.
- Moffitt, R., 1983. An economic model of welfare stigma. The American Economic Review 73 (5), 1023–1035.
- Moffitt, R., 1992. Incentive effects of the US welfare system: A review. Journal of Economic Literature 30 (1), 1–61.
- National Research Council and Institutes of Medicine, 2000. In: Shonkoff, J., Phillips, D. (Eds.), From Neurons to Neighborhoods: The Science of Early Childhood Development. National Academy Press, Washington DC.
- Parcel, T., Menaghan, E., 1990. Maternal working conditions and children's verbal facility: Studying the intergenerational transmission of inequality from mothers to young children. Social Psychology Quarterly 53, 132–147.
- Parcel, T., Menaghan, E., 1994. Early parental work, family social capital, and early childhood outcomes. American Journal of Sociology 99 (4), 972–1009.
- Rosenzweig, M., Schultz, P., 1983. Estimating a household production function: Heterogeneity, the demand for health inputs, and their effects on birth weight. The Journal of Political Economy 91 (5).

- Rosenzweig, M., Wolpin, K., 1994. Are there increasing returns to the intergenerational production of human capital? Maternal schooling and child intellectual achievement. The Journal of Human Resources 29 (2).
- Rosenzweig, M.R., Wolpin, K.I., 2000. Natural 'natural experiments' in economics. Journal of Economic Literature XXXVIII (4), 827–874.
- Ruhm, C., 2002. Parental employment and child cognitive development. NBER Working Paper No. 7666.
- Todd, P., Wolpin, K., 2003. On the specification and estimation of the production function for cognitive achievement. Economic Journal 113 (485), 3–33.
- Todd, P., Wolpin, K., 2005. The production of cognitive achievement in children: Home, school and racial test score gaps. Working Paper. University of Pennsylvania.
- Vandell, D., Ramanan, J., 1992. Effects of early and recent maternal employment on children from low-income families. Child Development 63 (4), 938–949.
- Waldfogel, J., Han, W., Brooks-Gunn, J., 2002. The effects of early maternal employment on child cognitive development. Demography May 39 (2), 369–392.