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Differences by Mother's Education in the Effect of Childcare on Child Obesity

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RAND LABOR AND POPULATION

Differences by mother's education in the effect of childcare on child obesity

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Abstract

Previous studies have found that adverse effects of maternal employment on child obesity are limited to mothers with higher education and earnings. Explanations for this have centered on differences between the childhood nutritional and exercise environments provided by non-parental caregivers versus by the mothers. The present study explores this non-parental care mechanism in a quasi-structural model of employment effects on child obesity transmitted through cumulative months of non-parental childcare over the child's pre-school years. Consistent with previous work, we find that children age 2-18 whose mothers have 16 years or more years of education have a 1.4-1.9% higher risk of obesity for each year of non-parental childcare. Additionally, however, we estimate that children whose mothers have less than 12 years of schooling have a 1.3-1.8 % *lower* risk of obesity for each year spent in a non-parental childcare setting. We interpret this new finding as due to positive selection into the workforce on ability in both home and market work.

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INTRODUCTION

Previous studies have found adverse effects of maternal employment on child obesity for mothers with higher levels of education and earnings but no effect for mothers with lower education and earnings (Anderson et al., 2003; Fertig et al., 2009; Ruhm, 2008). Improving our understanding of the nature of this apparent heterogeneity in the effects of maternal employment is important especially in light of the quite dramatic increases in employment among less educated women since the early 1990s, partly in response to reforms targeted at moving single mothers into the workforce (Meyer and Rosenbaum, 2001). The potential mechanisms through which the heterogeneity of maternal employment effects on childhood obesity are many, including breastfeeding and quality of post-weaning nutritional inputs, snacking versus regular meals, sport and other physical activity, and sedentary activities such as television watching (Fertig et al., 2009). Most generally, they will involve substitution of non-parental childcare for parental childcare. The present study estimates the cumulative effect of non-parental childcare up to age 5 by mother's education in a joint model of maternal employment, childcare, and obesity at ages 2 to 18.

A key problem that hampers research in this area is the complicated selection problem arising due to correlation of maternal employment and childcare inputs with unobserved characteristics of mothers and children and concurrent correlation of these unobserved factors with children's outcomes. First, working mothers whose children in non-parental childcare may differ systematically from working or non-working mothers whose children are not in non-parental childcare due to unobserved factors that also affect the child's risk of obesity. These factors may include the mother's or couple's preference for consumption relative to child investments, mother's ability in home work, the child's genetic dispositions towards obesity. Second, children's obesity may affect maternal employment and childcare decisions (a "reverse causation" phenomenon). Though most studies in the literature have recognized the existence of the first source of selection bias, the second source of bias has been largely ignored, with exception of Ruhm (2008). Anderson et al. (2003) and Cawley and Liu (2007) use an instrumental variables approach that deals with both sources of selection bias; however, in both studies the set of instruments used to identify the effect of maternal employment was weakly correlated with endogenous variables.

The present study differs from previous studies in several ways. First, its theoretical model incorporates the effect of maternal employment on child obesity through cumulative non-parental childcare experience (in months), adopting the same theoretical strategy used by Bernal and Keane (2010) to model the relationship between childcare and cognitive development. Instead of using the average hours spent in a non-parental childcare setting or more recent childcare inputs, as has been done in previous studies, our model uses cumulative non-parental childcare experience (in months). The rationale for using cumulative inputs in the child physical production function is analogous to that for cognitive ability production function (Bernal 2008). In particular, the use of cumulative inputs assumes that the effect of childcare is invariant with child's age and that only cumulative experience in childcare affects the child's physical production function. Second, the empirical model in this study is derived from the theoretical model by forming approximations to the mother's employment and childcare decision rules and child physical production function. This method is recognized as a quasi-structural approach in the literature (Bernal and Keane, 2010). The resulting joint model of the employment-childcare decision and the child production function allows both sources of selection bias discussed above to be addressed. Finally, we use data on maternal employment and child obesity in the U.S. from 1987 through 2007, covering a period during which employment rates among low-education mothers increased greatly.

We employ multiple identification strategies to identify the effect of non-parental childcare on child obesity. In our primary identification strategy, we use individual, time, and state variations in Earned Income Tax Credit (EITC). In the mid-1990s the generosity level of the EITC was increased significantly throughout the U.S., and several states adopted supplementary benefits in addition to federal credit. The increase in benefit generosity and its explicit link to earnings resulted in substantially greater labor force participation rates among single mothers (Meyer and Rosenbaum, 2001). However, at the same time, EITC benefits reduced married women's employment (Eissa and Hoynes, 2004), and effectively subsidized married mothers to stay at home. Because the children in our study were born between 1987 and 1997, we are able to observe both single and married mothers' employment and childcare decisions during their children's early years of life before and these increases in EITC generosity. We believe that changes in federal and state EITC rules will therefore provide a good source of variation across time and individuals. We simulate the EITC benefit level for each household adjusting for the number of dependents in the household and conditional on eligibility criteria such as employment and household income using both federal and state EITC rules.

The variation in the EITC is not the only source of exogenous variation exploited in this study for identification purposes. We also incorporate into the empirical model other exclusion restrictions suggested by the literature (James-Burdumy, 2005; Bernal and Keane, 2010) such as fluctuations in local market conditions (state unemployment rate, the percentage of women in service occupations, and average wages). We confirm that EITC benefits and local market conditions are valid exclusions in a number of over-identification tests.

The battery of over-identification tests shows that the set of exclusion restrictions correlate with the main outcome of the model only through cumulative childcare inputs. This implies that we could safely use the instrumental variables (IV) method instead of the quasi-structural approach in our study. Our quasi-structural approach, however, additionally allows an economic interpretation for the childcare parameter in the child physical production function. For example, changes in EITC rules may have affected not only the cumulative time spent in childcare but also the parental inputs in form of goods. The latter relationship between EITC rules and the cumulative time spent in childcare and parental investment in form of goods can be seen from our theoretical model. In the standard IV approach this complex relationship wouldn't be directly recognizable.

The major findings of the study concern the heterogeneity of effects of non-parental childcare on obesity by maternal education. Consistent with previous work, non-parental childcare is found to have adverse effects on child obesity for mothers with a college degree and higher. Unlike in previous studies, however, we find additionally that children of less educated mothers (high school diploma and below) benefit from being placed in a non-parental childcare setting, having a significantly lower risk of obesity compared to children in full-time parental care. We discuss this finding as being consistent with positive selection into the workforce on ability in both home and market work among women with no more than a high school education.

This paper is structured as follows. The next section provides background. Section III demonstrates the theoretical model and derives the empirical model and discusses the method of estimation. Section IV discusses the data. The main empirical results are discussed in Section V. We conclude in Section VI.

II. BACKGROUND

We begin this section by discussing methods, findings, and shortcomings of the studies that explore the direct effect of maternal employment on child obesity. Then we discuss the possible mechanisms that link maternal employment with child obesity in order to show that non-parental childcare plays a significant role in this complicated relationship. Recent studies in the literature all employ similar empirical models of the relationship between maternal employment and child obesity. The parental inputs in the form of maternal average weekly work hours over the entire child's life are assumed to be linearly related to child's weight status. As a measure of child's weight status, which enters as a dependent variable in the models, the studies either use a continuous measure of Body Mass Index (BMI) or a BMI-based indicator of obesity or overweight status using Centers for Disease Control (CDC) growth charts. Child characteristics such as gender, age, race, birth weight, whether born before due date, and whether breastfed, along with maternal characteristics such as age, marital status, education and an indicator of employment before pregnancy, are used as additional explanatory or control variables in most empirical models. Finally, each of these studies explicitly or implicitly recognizes that maternal employment in the child obesity equation may be correlated with child and family unobserved characteristics (unobserved by the researcher but known by the mother) and that if these correlations are not appropriately addressed the maternal employment parameter in the obesity equation would be biased. Methods used to address the endogeneity problem have included observing the same child at different ages or pairs of siblings at the same time and differencing out unobserved factors using a fixed effect estimator (Anderson et al., 2003; Scholder, 2008), and using an IV approach (Anderson et al., 2003). Observed proxies for unobserved characteristics have also been used (Scholder, 2008; Ruhm, 2008).

The magnitude of the effect of maternal employment on child obesity varies substantially across studies. A strong, statistically significant effect of maternal employment on child obesity has been found only when unobserved heterogeneity has been either ignored (Anderson et al., 2003; Fertig, 2009; Herbst and Tekin, 2009), or approximated by variables such as HOME score (Ruhm, 2008) or the mean maternal work status over all ages of the child (Scholder, 2008). When fixed effect or IV estimators were introduced to deal with the endogeneity of maternal employment in the obesity equation, the effect of maternal employment disappeared (Anderson et al., 2003; Scholder, 2008). Each of these estimation methods has important disadvantages. The use of proxies as approximations for unobserved child and maternal characteristics will not always help to solve the above selection problem. In the situation when the proxy is contaminated with non-classical measurement errors, exacerbation of the bias may result (Todd and Wolpin, 2003). The use of a fixed effect estimator, on the other hand, may lead to the significant loss of degrees of freedom, reduction in the variability of covariates, and exacerbation of the effect of measurement error in explanatory variables (Angeles, Guilkey and Mroz, 1998; Angrist and Pitchke, 2009). Previous studies in the majority of cases deal with relatively small samples of children or sibling pairs and it is not surprising that they fail to find any statistically significant effect, not only for maternal employment but for any of the covariates in their models.

In the presence of both selection problems discussed above, the IV approach nevertheless produces unbiased estimates of the effect of maternal employment on child obesity if a set of instruments satisfies the criteria of validity and relevance of instruments. The first condition is of a strong rather than weak correlation of exclusion restrictions with an endogenous variable (childcare experience) and the second condition is the absence of significant correlation with unobserved factors. These conditions are not easily met. Anderson et al. (2003) used state unemployment rate, childcare regulations, average wages of childcare workers, welfare benefit levels, and the status of welfare reform as instruments, but found that they were weakly correlated with maternal employment. This led to a large increase in standard errors.

Two recent studies (Fertig et al., 2009; Cawley and Liu, 2007) attempt to unravel possible mechanisms through which maternal employment might adversely affect child obesity. Both studies provide evidence that nutrition and supervision play significant roles in the relationship between maternal employment and child obesity. For instance, Fertig et al. (2009) demonstrate that maternal employment is related to child's BMI through the average number of meals consumed in one day, through reading/talking/listening to music, and through TV watching. Most relevant for our study, they also find for mothers with more than 12 years of education that maternal work hours are positively associated with the use of non-parental childcare and the latter is associated with higher child BMI. Using a different approach, Cawley and Liu (2007) show that maternal employment is associated with a lower probability of doing any cooking, eating, or playing with the child, engaging in childcare, and supervising the child. The interpretation in these studies is implicitly or explicitly that parental time is superior to the time of a non-parental caregiver. We argue that this is more likely to be true for highly educated parents than for parents with lower educational attainments, and that parental caregiving may therefore be simultaneously less obesigenic for the children of high-education parents and more obesigenic for the children of low-education parents.

III. MODEL

We present now a theoretical model of the production of child weight status in which the childcare effect on obesity includes two components: the effect of time spent with own mother relative to time spent in non-parental childcare; and the effect of any change in goods inputs that the mother chooses because of using childcare. This is similar to Bernal and Keane (2010) who investigate the effect of childcare on child cognitive development.

We embed the child obesity equation within a dynamic model of the maternal employment and childcare decisions. This dynamic model shows that the time-varying exogenous rules of the EITC program and changes in the local labor market affect child obesity indirectly through maternal employment and childcare. Based on this theoretical model, we elaborate our empirical model by forming approximations of the maternal employment and childcare decision rules and estimating them simultaneously with the child obesity equation using the discrete factor method (Mroz and Guilkey 1995; Mroz 1999). This method avoids the restrictive joint-normal assumption on the distribution of unobserved factors. Compared to an IV estimator, the discrete factor method provides more efficient estimates, especially for more moderate-sized samples.

In our theoretical model, a mother makes choices about employment and childcare each period starting from child's birth until the child enters kindergarten. Suppose that in each period the mother has two work options (work or not) and two childcare options (use non-parental childcare or use parental care). We take advantage of our being able to observe in our data the total number of months that the children attended non-parental childcare before they enter kindergarten. Therefore we specify here a period of one month. We denote the choice set as:

$$J = \{(h_t, e_t); h_t = 0,1; e_t = 0,1\} \tag{1}$$

$$e_t = \begin{cases} 0 & \text{parental care} \\ 1 & \text{non-parental childcare} \end{cases} \qquad h_t = \begin{cases} 0 & \text{not working} \\ 1 & \text{working} \end{cases}$$

The mother's current utility function given the choice of work and childcare option *j* and choice-specific shock ε_t^j embodies Constant Relative Risk Aversion (CRRA) in consumption c_t:

$$u_t^j = \frac{c_t^{\alpha_1}}{\alpha_1} + \alpha_2 I[e_t = 1] + \alpha_3 I[h_t = 1] + \alpha_4 \frac{A_t^{\lambda} - 1}{\lambda} + \varepsilon_t^j \tag{2}$$

In the above utility function, α_1 is the coefficient for risk aversion, α_2 is mother's taste for childcare, and α_3 is mother's taste for work. A_t is a measure of child's physical development in which a low level of A_t implies high adiposity and a higher likelihood of being obese. Mothers get utility α_4 from a high level A_t of the child according to a

CRRA function with parameter λ. Therefore $\lambda < 1$ implies diminishing marginal utility from lower child adiposity. A mother would therefore have an incentive to use her time and monetary resources to obtain utility that compensates her for the disutility from additions to the risk of her child's obesity.

The mother also faces in each period a budget constraint of the following linear form:

$$c_t = y_t + 180 w_t h_t - cc \ * I[e_t = 1] + G((\hat{I}(w(z), h(z), y(z)), R(z)) \qquad (3)$$

According to (3), the mother receives spousal labor income y_t each period. We assume that income is stochastic and follows a first-order Markov process. Its distribution $F(y_t \mid y_{t-1})$ is known to the mother. The cost of childcare cc is time invariant. The mother's wage in period t is denoted by w_t and 180 is the maximum number of hours per month that the mother supplies if she chooses to work full-time in period t. G is the EITC amount per quarter, which is a function of $\hat{I}_t$, being cumulative income of the household in year z, and of EITC parameters set by federal and state governments. In reality, EITC is also a function of the number of dependents in the household; however, for sake of simplicity, we assume that the mother has only one child in this model.

The child's adiposity is a function of the time spent in childcare $\hat{E}_t$, time spent with parents $\hat{M}_t$, cumulative parental investment in a form of goods $\hat{P}_t$ in period t, and mother's unobserved ability in home work ϕ,

$$A_t = A_0 + \beta_1 \hat{E}_t + \beta_2 \hat{M}_t + \beta_3 \hat{P}_t + \phi \qquad (4)$$

Assuming that time passed since child birth combines both cumulative time spent with parents and time spent in non-parental childcare setting at period t (that is, $\overline{T}_t = \hat{E}_t + \hat{M}_t$), then (4) becomes

$$A_t = A_0 + (\beta_1 - \beta_2)\hat{E}_t + \beta_2\overline{T}_t + \beta_3\hat{P}_t + \phi \tag{5}$$

A_0 is the child's initial measure of child's adiposity which is a function of child's birth weight, sex of the child, mother's age and education at birth, mother's BMI and her participation during pregnancy in a variety of welfare programs such as WIC and Food Stamps. All these observed characteristics are included in a vector X. The child's initial measure of child's body structure also depends on child's time-invariant innate risk of obesity μ. In this model, we implicitly assume that the mother knows the child's innate risk of obesity and form of the low adiposity production function,

$$A_0 = \mu + X\gamma \tag{6}$$

The cumulative parental investment in the form of goods at time t is:

$$\hat{P}_t = \pi_0 + \pi_1\mu + X\pi_2 + \pi_3\hat{E}_t + \pi_4 \ln(\hat{I}_t) + \pi_5\overline{T}_t + \xi \tag{7}$$

where $\hat{I}_t$ is a cumulative income of the household, and ξ is mother's taste for investments in the form of goods. The latter heterogeneity across mothers could be a result of different preferences for child quality (Bernal and Keane, 2010). Substituting (6) and (7) into (5) yields the following expression for the child's (low) adiposity:

$$A_t = \alpha_0 + X\alpha_1 + \alpha_2 E_t + \alpha_3 \ln(\hat{I}_t) + \mu + \phi + a_4\xi \tag{8}$$

Unfortunately, a direct measure of the child's adiposity is not available in the data. Instead, we observe his or her BMI. We assume that BMI measures adiposity with error ε_t. Denoting the resulting measure by O_t, the child physical production function is then assumed to have the following linear form:

$$O_t = qA_t + \varepsilon_t = \tilde{\alpha}_0 + X\tilde{\alpha}_1 + \tilde{\alpha}_2 E_t + \tilde{\alpha}_3 \ln(\hat{I}_t) + \eta + \varepsilon_t \tag{9}$$

For the tractability of our theoretical model, we assume that $q = -1$. The childcare effect on BMI is $\tilde{\alpha}_2$. Although in our data the childcare variable E_t is simply months in non-parental childcare, the coefficient $\tilde{\alpha}_2$ combines the effect of time spent with own parents relative to time spent in childcare, minus the effect of any change in goods inputs that the parents choose because of using childcare.[3] Finally, η is a combination of child unobserved heterogeneity, μ, mother's unobserved ability in home work, ϕ, and mother's taste for investments in the form of goods, ξ.

The deterministic state variable which the mother faces each period is given by E_{t-1}. Furthermore, there are state variables which evolve exogenously such as welfare rules R_t. There are also a set of time invariant state variables in X and η.

The mother's optimization problem can be expressed as a series of one-period problems using Belman's principle of optimality (Rust, 2008). The choice-specific value function is given by the following expression, which assumes that the utility shock follows the multivariate extreme value distribution where σ_2 is a common scale parameter:

$$\tilde{V}_t^j(s_t) = u^j(c_t, h_t) + \varepsilon_t^j + \beta\left[\int_{y_{t+1}} \sigma_2 \log\left(\sum_{k=1}^{K} \exp\left\{\tilde{V}_{kt}(s_{t+1}, y_{t+1})/\sigma_2\right\} + \gamma\right) dF(y)\right] \tag{10}$$

[3] Using simple algebra $\tilde{\alpha}_2 = q(\beta_1 - \beta_2 + \pi_3\beta_3)$ and assuming that $q = -1$ then $\tilde{\alpha}_2 = \beta_2 - \beta_1 - \pi_3\beta_3$.

Based on (10), the optimal employment and childcare decision rules is the function of all state variables that enter in the above value function:

$$\Pr(d_t^* = d) = \frac{\exp(\widetilde{V}(s_t \mid d_t^* = d))}{\sum_{k=1}^{4} \exp(\widetilde{V}(s_t \mid d_t^* = k))} \tag{11}$$

where $d = \begin{cases} 1 \text{ - no work and parental care} \\ 2 \text{ - no work and non - parental care} \\ 3 \text{ - work and parental care} \\ 4 \text{ - work and non - parental care} \end{cases}$

In the literature, more emphasis is given to exploring the effect of maternal input choices on the upper tail of the child BMI distribution, and especially to the 95th percentile and above of the BMI distribution. According to the CDC recommendations, these children are considered obese. The probability that the child is obese can be given by the following logit equation.

$$\Pr(O_t^* = 1) = \frac{1}{1 + \exp\left(-\left(\widetilde{\alpha}_0 + X\widetilde{\alpha}_1 + \widetilde{\alpha}_2 E_t + \widetilde{\alpha}_3 \ln(\hat{I}_t) + \eta\right)\right)} \tag{12}$$

From the above specifications, we can see that welfare rules R_t enter employment and childcare decision rules and affect child's physical development only through cumulative childcare inputs. For welfare rules R_t to be valid instruments for estimating the risk of obesity both variables must be uncorrelated with η.

The empirical strategy of this study is to jointly estimate (11) and (12) assuming M points of support to approximate the distribution of η. There are four equations in the model; therefore, η_k consists of four vectors each representing the set of heterogeneity parameters in one of the equations. Conditional on mass point $\eta_m = (\eta_{1m}, \eta_{2m}, \eta_{3m}, \eta_{4m})$, mother-child pair i contributes to the likelihood function as follows:

$$A_{im}(\eta_m) = \prod_{t=1}^{T}\left[\prod_{j=1}^{3} P(d_{it} = j \mid \eta_{jm})^{d_{it}}\right] P(O_{it} = 1 \mid \eta_{4m})^{O_{it}} \left(1 - P(O_{it} = 1 \mid \eta_{4m})\right)^{1-O_{it}} \qquad (13)$$

The unconditional contribution for mother-child pair i is:

$$A_i = \sum_{m=1}^{M} \varphi_m A_{im} \qquad (14)$$

Where φ_m is a weight of mass point η_m. Finally, the likelihood function can now be written as follows:

$$L = \prod_{i=1}^{I} A_i \qquad (15)$$

The likelihood function is maximized with respect to all parameters as well as the individual's specific mass points and weights. In each equation, we also include a constant term and normalize the individual mass point per equation to zero in order to identify the model.

Finally, we compute a robust covariance matrix using methodology discussed in Train (2003):

$$\operatorname{cov}_\theta \hat{\theta} = [-L''(\hat{\theta})]^{-1}[L'(\hat{\theta})'L'(\hat{\theta})][-L''(\hat{\theta})]^{-1} \qquad (16)$$

where $L'(\hat{\theta}) = \dfrac{\partial L(\theta)}{\partial \theta}$ is a gradient vector and $L''(\hat{\theta}) = \dfrac{\partial^2 L(\theta)}{\partial \theta^2}$ is a Hessian matrix both evaluated at $\hat{\theta}$.

Our approach is structural and therefore we use unweighted estimators assuming the absence of endogenous stratification. Cameron and Trivedi (2005) note that there is minimal efficiency loss when ignoring sample clustering in the case that cluster effects are random.

We interpret the unobserved heterogeneity terms in the following way, taking into account previous work by Anderson et al (2003) and others, whose detailed treatment we reserve for the Conclusion section. Unobserved heterogeneity in the theoretical model has three components: mother's idiosyncratic preference for investment in the form of goods, mother's unobserved ability in home work, and child's innate disposition toward obesity. Heterogeneity in the second unobserved component across mothers may be associated with mothers' varied abilities in production of home goods that are associated with child development. Suppose hypothetically mothers can be divided into two equal groups: the first group representing high ability mothers in home work and the second group representing low ability mothers in home work. If high ability mothers in home work are also high ability mothers at market work (employment), then they may be more likely to work (and by necessity use childcare) than the second group of mothers. If higher ability in home work includes skills in obesity-preventing childrearing, then the childcare effect would be contaminated by a positive term in the model that does not control for unobserved heterogeneity. This follows in the linear model $p\lim\alpha_2 = \tilde{\alpha}_2 + \frac{E\{E_t,\phi\}}{V\{E_t\}}$ with the last term being positive due to the positive correlation between months in childcare and mother's unobserved ability in home work.

IV. DATA

We use the Panel Study of Income Dynamics (PSID) Core and Child Development Supplement (CDS) as our main data source (Institute for Social Research 2010). We use

PSID Core file to create a work history for each mother that tracks her employment status from the month of birth to the month when the child enters kindergarten (see Appendix), and to code maternal socio-demographic and health characteristics. We use CDS waves I, II, and III, respectively in 1997, 2002/03, and 2007, to create the childcare history of each child and to code child characteristics including BMI.

In order to understand our sample selection strategy a brief background on the PSID Core and CDS is needed. The PSID has followed the same families and their descendants since 1968 and it has substantial information on the socioeconomic status of respondents for more than four decades. The PSID consists of two separate samples: the University of Michigan Survey Research Center (SRC) and Survey of Economic Opportunities (SEO) samples. Originally, in 1968 the SRC sample was an equal probability sample of 2,930 family units. The SEO sample size then comprised 1,872 low-income families. Because children born to a member of the original families were tracked as separate family units as soon as they separated from their original families, by 1996 the number of families in the PSID Core was over 8,700.

The PSID CDS was first conducted in 1997 and was an addition to the PSID core data collection. The PSID CDS I collected data on children ages 0-12. The majority of respondents were from original PSID families. Respondents from an "Immigrant sample" were added to the PSID Core in 1997. Additionally, the CDS I included a group of African-American families which were not part of the PSID Core in 1997 (about 500 children).

[TABLE 1 ABOUT HERE]

Table 1 shows the sample selection criteria used in this study. Wave I of the CDS was first administered in 1997 and information on randomly selected 3,563 children of the PSID family units was collected. The majority of these children were again assessed in wave II in 2002/2003 and wave III in 2007.[4] We excluded the 271 children for whom the primary caregiver of CDS I was not the biological mother. We also restricted our sample to children who were born after 1987. For the 690 children born before 1987, in 1997 when Wave I interviews were conducted, more than four years had passed since they entered kindergarten raising the possibility of recall bias. For 397 children their mothers were not heads of PSID Family Units or wives or cohabiters of the heads and therefore employment histories were not collected. While this latter group has been shown to be more frequently found in poor and welfare-receiving households (Rendall 1997), the relatively small number of cases involved here reduces the likelihood of biases due to their omission from our study sample. For 55 children, employment information of their mothers is interval-censored, and for 207 children a variety of maternal and family characteristics are missing. Finally, for 132 children, information on state of residency is undeterminable in the PSID Core. Dropping all the above children from our sample results in a sample of 1,941 mother-child pairs.

We next discuss the way the childcare variable is constructed for children in our sample. Every primary caregiver in the CDS is asked whether the child has experienced non-parental childcare prior to starting kindergarten. If a primary caregiver provides an affirmative answer for this question, then she is followed up with the set of questions

[4] The response rate in the CDS-II was 84% and in the CDS-III 90% according to CDS-III User Guide.

related to each arrangement (up to twelve arrangements) such as type of arrangement, age of the child when a given arrangement started and stopped. In addition to this information, every caregiver provides information whether the child attended any pre-school setting or head start program and age when the child started and stopped a given program. Using all the above information, we create a monthly indicator of non-parental childcare use for every child starting from the month when a child was born up to the month when the child started kindergarten.

[TABLE 2 ABOUT HERE]

The outcome variable in our analysis is child's BMI. The weight and height of the child were measured by the interviewers in the 2002/03 and 2007 waves (CDS II and III). The weight and height were partly measured and partly reported by primary caregivers in the 1997 wave (CDS I). The CDS provides both continuous and categorical measures of BMI (underweight, normal weight, overweight and obese) for children whose age is 4 years or above. The categorical measure of BMI in the PSID CDS is computed using recommendations of Center of Disease Control growth charts. For 2-3 year olds, we first computed continuous measures of BMI based on reported or measured weights and heights of the children and then transformed them into categorical measures of BMI using the CDC charts. As shown in Table 2, we have 4,040 observations of BMI for 1,941 children. For 327 children we observe BMI only once, for 871 children we observe BMI twice, and for 657 children, BMI is observed in all three CDS waves. We do not observe BMI for 86 children. However, we don't drop these children from our analysis because they still possess valuable information on maternal employment and non-parental childcare use up to entering kindergarten.

[TABLE 3 ABOUT HERE]

Table 3 shows the age distribution of children on the date of the CDS interview when the components of BMI are reported or measured. The median age at assessment is nine years. Because the mean age is only slightly higher than the median age (not shown) and taking into consideration that nine is the second most frequent age of children on the day of assessment in our sample (7.85%), we consider the age distribution of BMI measure to be approximately normally distributed. This implies that for the empirical analysis age at assessment does not require any further transformation.

[TABLE 4 ABOUT HERE]

Table 4 provides cross-tabulations of maternal employment and childcare use at 3, 24, 48, and 60 months by maternal education. This table demonstrates that the rates of return to work and use of non-parental childcare are heterogeneous across educational groups. Differences in those rates are especially large between the group of mothers with below high school education and the other education groups. For example, at 3 months only 18% of mothers with below high school education return to work. For more educated mothers the rate of return to work is substantially higher than for the latter group of mothers. The proportion of mothers who worked at 3 months is 35.5% for those who completed high school, 37.8 % for those with some college education, and 46.7% for mothers with bachelors or advanced degrees. The rate of non-parental child care use is also lowest for less educated mothers. Of those with below high school education only 15% place their infants in non-parental child care in the first three months. This number is substantially higher for more educated mothers, ranging between 35 and 40%. A 20% differential in working and non-parental child care use between the group of mothers with below high school education and the other educational groups is seen again at 24 and 48 months old. These differences in non-parental care associated with maternal employment make the modeling of the selection process into maternal employment especially important. In particular, they suggest that low-education mothers who are employed while their children are very young are an especially selective group.

[TABLE 5 ABOUT HERE]

Table 5 compares the characteristics of obese and non-obese children at ages 2 to 18 in any of the three CDS waves (weighted using the child level sample weights). The 828 child-years with BMIs above 95th percentile constitute about 20 percent of our total child-year sample. The average non-obese child is more likely to live in a family with both parents present. Mothers of non-obese children are on average older and more educated and have significantly lower BMI than mothers of obese children. Mothers of non-obese children are less likely to participate in WIC and Food Stamp programs during pregnancy and have higher family incomes. Obese children are more likely to be male, Black or Hispanic, and be born before due date. Obese children have higher birth weights on average than do non-obese children. Finally, obese children overall spend slightly more time in any non-parental childcare setting (24.7 months) than non-obese children (22.6 months).

For identification purposes, we also construct a value of the Earned Income Tax Credit (EITC) for each family unit. In Appendix Table A1 we report EITC rules for period 1987-2001, which we use for simulation of benefits. Though EITC is a federal program, there is substantial variation across the states. Ten states in the U.S. provide additional refundable benefits in addition to the EITC federal benefits. The year when the additional refundable benefits were adopted differ by states. For example, Vermont has been paying 32% of federal credit since 1988, while New Jersey adopted 15% additional payments only in 2000 (see Appendix Table A2). Furthermore, 5 states adopted non-refundable credits at different periods. Using EITC rules and conditional on income and number of dependents in the family unit, we simulate the federal EITC and the state refundable credit amount for each mother-child pair in our sample for every year. Additionally, we create a supplementary instrument, which is the amount of non-refundable credit for each mother in a given year.

[FIGURE 1 ABOUT HERE]

Figure 1 shows that the average simulated EITC benefit amount (shown in 1988 dollars) has been increasing continuously since 1987. However, since 1994 the rate of increase in the average EITC has been much higher than it was before 1994. We also use other theoretical exclusion restrictions associated with local labor market conditions for the purpose of identification. Though the local labor market conditions can be directly identified using the PSID files, we rely on other external data sources and merge them with our sample. In particular, we use Department of Labor databases to bring in our sample the monthly and seasonally adjusted state unemployment rate. From Bureau of Labor and Statistics (1987-2007) we use information on the monthly state average wage at 20th percentile and employment rate in service occupations among women. From the latter source, we also extract Consumer Price Indices to normalize all variables measured in dollars to 1988 dollars.

V. RESULTS

Before turning our attention to main findings of the empirical model, we first discuss results of two hypotheses tests to provide evidence of validity and relevance of employed exclusion restrictions for our instrumental variables. In particular, according to the first hypothesis, the exclusion restrictions are irrelevant ones if there is no correlation between them and maternal employment and childcare experience. According to the second hypothesis, the exclusion restrictions are valid if there is no correlation between them and child obesity. Thus, the rejection of the first and failure to reject the second hypothesis provide good evidence that proposed exclusion restrictions in the empirical model satisfy these two important criteria.

[TABLE 6 ABOUT HERE]

To test both hypotheses we use a Wald test. The motivation of the Wald test is that if the null hypothesis of the test is true, then estimates received from the unconditional maximum likelihood estimation must satisfy restrictions of the null hypothesis, so the Wald statistics should be close to zero. Table 6 represents results for Wald tests of both hypotheses testing. The p-value ($p<0.01$) of the first Wald test statistic (78.14) rejects hypothesis that exclusion restrictions do not have any significant explanatory power in the maternal employment and non-parental childcare equation. At the same time, the p-value ($p=0.581$) for the second Wald test statistic (4.37) demonstrates that we fail to reject the null hypothesis that the exclusion restrictions are jointly equal to zero in the obesity equation at conventional significance levels. These all imply that theoretical exclusion restrictions have impacts on child obesity only through childcare and employment.

[TABLE 7 ABOUT HERE]

Table 7 provides estimates of the joint estimation of obesity and childcare-employment equations. We first discuss findings for the work and childcare choice equations. First, the theoretical model suggests that the cumulative employment and childcare experience affect the current work and childcare choices of mothers. As expected, the results show that the high work experience increases the likelihood in working in the current period. Furthermore, cumulative non-parental childcare experience is associated with increased use of childcare in the current period. However, the most important results are for the theoretical exclusion restrictions in the work and childcare choice equations. First, our results confirm that the EITC increases the employment prospect of single mothers relative to married mothers. The negative and statistically significant estimates for the interaction term between the EITC and whether mother was married at birth in the working/parental childcare and working/non-parental childcare equations are consistent with the finding of Eissa and Hoynes (2004) that the EITC effectively subsidizes married mothers to stay at home. Other notable findings for theoretical exclusion restriction variables are: 1) during periods of high unemployment mothers are less likely to work and use parental care; and 2) in states with a high percentage of workers in service industry, mothers are less likely to use the work/parental care option relative to other available options.

The results of Table 7 are largely as expected with respect to child, maternal, and household characteristics associated with child obesity. As has been documented in the public health literature, Hispanics and Blacks have higher risk of obesity than non-Hispanic Whites, with Hispanic children having the highest obesity probabilities (Ogden et al., 2010). Higher maternal BMI is associated with higher probability of child obesity, which is also well documented in the literature (Salsberry and Reagan, 2005). Higher child birth weight and premature birth are also associated with greater likelihood of obesity in childhood, consistent with other literature (Maher et al., 2008), and boys are more likely to obese than girls, as been found especially for African-American children (Ogden et al., 2010). We find no association between Food Stamp participation during the pregnancy and future probability of obesity, which is expected given previous findings of either no association (Hofferth and Curtin 2005) or positive contemporaneous associations of Food Stamp participation and child obesity (Jones et al., 2003).

The major question addressed by our study is whether the effect of childcare on child obesity differs for mothers with different levels of educational attainment. Due to the relatively small sample size, we do not estimate separate models for different maternal education subgroups as has been done in previous studies (Anderson et al., 2003; Fertig et al., 2009; Ruhm, 2008). Instead, we estimate the model with interactions between maternal education dummies and months of non-parental childcare experience. In particularly, we break down education into the four subgroups of less than high school diploma (below 12 years of education), high school diploma (12 years of education), some college (13 to 15 years of education), and bachelors and advanced degrees (16 and more years of education). Using this specification for years of education in the model, we find that higher the mother's education, the less likely is the child to be obese, consistent again with previous literature (Anderson et al., 2003; Ruhm, 2008).

The main effect of education on obesity is negative, and monotonically so, across the four educational attainment subgroups. Consistent with previous studies, the sign of the coefficient for months of childcare is positive for the reference group mothers with 16+ years of schooling, though it is not statistically significant. Also consistent with previous studies are the negative signs on the coefficients for the interaction of both the <12 years and 12 years of schooling, and the magnitudes of these coefficients more than cancel out the positive reference-group effect. The interpretation of coefficients in non-linear models especially in the non-linear models with interaction terms, however, is not straightforward and requires additional computation to conduct valid statistical tests (Ai and Norton 2003). Therefore, to quantify the effect of non-parental childcare by maternal education we use a simulation method. In particular, we assume that the entire set of estimated coefficients, mass points and mass point probabilities follow a multivariate normal distribution centered at the estimated values of the parameters with covariance matrix equal to the estimated covariance matrix for the entire set of parameters. Then we draw a set of normally distributed random variables from this distribution and recalculate the outcomes of the model with perturbed parameters. The above step is iterated 100 times and the average values for the main outcomes of the model such as the probability of obesity, childcare and work experience is computed. Table 8 compares the simulated averages with the actual averages for the main outcomes of the model. The p-values of the test of equal means with unequal variances show that we cannot reject hypothesis that the simulated means are equal to the observed means. This implies that our model fits the observed data well enough to perform the above simulation exercise.

[TABLES 8 AND 9 ABOUT HERE]

In Table 9 we report simulated probabilities of obesity by maternal education and childcare experience. In Figure 2, we provide a graphical display of simulated probabilities with computed 95 percent confidence intervals. The simulated probability of obesity for the average child of the mothers with less than 12 years of schooling is 0.276 when the child has no exposure of non-parental childcare. The greater the child's total exposure to non-parental childcare, the lower is the probability of obesity. After 60 months in childcare, the probability of obesity declines to 0.198. We observe a similar decline for the average child whose mother has only a high school diploma. With no experience in non-parental childcare, the probability of obesity is 0.245; after 24 months in a non-parental childcare setting the probability of obesity declines to 0.211, and after 60 months it is 0.167.

For the average child whose mother has between 13 and 15 years of schooling, however, the probability of obesity increases slightly with non-parental child experience. For example, the probability of obesity is 0.228 with no childcare experience and it is 0.240 after 60 months in a non-parental childcare setting. Finally, for a child whose mother has at least a bachelors degree, the probability of obesity steadily increases substantially as the child spends more time in a non-parental childcare setting. With no experience in any non-parental childcare setting, the probability of obesity is only 0.131, after 36 months in childcare, the probability goes to 0.176 and it further increases to 0.212 after 60 months in non-parental childcare.

[FIGURE 2 ABOUT HERE]

To understand better the reasons for this requires more understanding how unobserved heterogeneity affects our estimates. Table 10 provides estimates from the obesity equation estimated without controlling for unobserved heterogeneity. Comparing the effect of childcare from this table with the same effect from Table 7 it can be seen that after accounting for non-random selection of mothers into employment and non-parental childcare by unobserved factors in the obesity equation, the effect of childcare decreases from 0.016 to 0.010 and the interaction effects decreased only by 0.001 with the exception of the interaction effect for the child of the woman with some college education. Using conventional methods of computing the marginal effect of a continuous variable and its interaction effect with a categorical variable in a logit equation,[5] we find that the combined marginal effect of one month of childcare on the probability of child obesity has changed from 0 to -0.15 percent for a child whose mother has below 12 years of education, from -0.04 to -0.17 percent for a child whose mother has a high school diploma, from 0.14 to 0.02 percent for a child whose mother has some college and finally, from 0.24 to 0.13 percent for a child whose mother has a college diploma or higher. The largest change is therefore for the effect of a child whose mother has less than 12 years schooling.

[TABLE 10 AND FIGURE 3 ABOUT HERE]

To provide a better picture of importance of unobserved heterogeneity in the obesity equation, in Figure 3 we display the simulated probabilities of obesity across all four groups. The graph shows that control for non-random selection of mothers into employment and childcare has changed substantially the profile of the obesity prevalence across all groups, but that the largest changes have occurred for children of mothers with less than 12 years schooling or with a high school diploma. When unobserved heterogeneity is ignored in estimation of parameters of the obesity equation, no association between childcare and the probability of obesity for lowest educated women

[5] The marginal effect of childcare in the obesity equation is computed using conventional method:

$$\frac{\partial P(O_{ijt}=1\mid\eta_{4,m})}{\partial E_t}=\sum_{m=1}\varphi_m P\left(O_{ijt}=1\mid\eta_{4,m}\right)\left(1-P\left(O_{ijt}=1\mid\eta_{4,m}\right)\right)\widetilde{\alpha}_2$$

Each interaction effect is computed using the method suggested by Norton, Wang and Ai (2004) when one continuous variable and one dummy variable are interacted incorporating the individual's specific mass points and weights. The exact mathematical expression of the interaction effect is available from the authors upon request.

is found. For women with 12 years of education this association is only marginal. These findings match well with the earlier findings of Fertig et al. (2009) who also using a sample of children from PSID-CDS find no relationship between childcare and child obesity for both groups of mothers. The analogous comparison of the probabilities for more educated women demonstrates that accounting for unobserved heterogeneity eliminates the effect for women with some college education and it slightly flattens the obesity trajectory for women with college degrees.

VI. CONCLUSION

In previous studies, adverse effects of maternal employment on child obesity have been found for mothers with higher education and earnings, but no effects for women with low to medium education levels or earnings (Anderson et al., 2003; Fertig et al., 2009; Ruhm, 2008). Explanations for the heterogeneity of effects by maternal educational attainment have centered on differences between the childhood nutritional and physical activity environments provided by non-parental caregivers versus by the mothers. We explored this non-parental-care mechanism explicitly in a quasi-structural model of employment effects on child obesity transmitted through cumulative months of non-parental childcare over the child's pre-school years, using 1988-2007 waves of the PSID. The joint estimation of labor supply, demand for childcare, and child's obesity using exogenous variations in the EITC rules and local labor market conditions as identification criteria allowed us to estimate the employment effect through childcare. Our main estimate, of the effect of cumulative non-parental childcare on obesity, can be interpreted as due to a combination of the effect of time spent with own mother relative to time spent in non-parental childcare and the effect of any change in goods inputs that the mother chooses because of using childcare.

Consistent with the direction of effect in previous studies, we found that children whose mothers had a college diploma or advanced degree, if placed in a non-parental childcare setting, would have a 1.4-1.8 % higher risk of obesity at the same ages. Additionally, however, we found that children whose mothers had 12 years of education or below if placed in a non-parental childcare setting for one year would have a 1.4-1.9 % lower risk of obesity at ages 2-18. This latter result we found was due to unobserved heterogeneity effects that were larger for women with 12 years of education and below. In particular, the flat relationship between months of childcare and probability of child obesity found when estimating the model without modeling the selection of women into employment and childcare turned into a strongly inverse relationship between months of childcare and probability of child obesity when modeling this selection. For the children of college graduate mothers, the strong positive relationship between months of childcare and probability of child obesity in the model without unobserved heterogeneity was reduced in its magnitude when modeling selection into employment and childcare, but the relationship remained positive.

Although taken together these findings are new, we argue that they are consistent both with the explanations previously offered to explain why only for higher-educated women have adverse effects of maternal employment on child obesity been found, and also with limited other evidence on favorable effects of center childcare targeted at the children of low-income families. Anderson et al. (2003) explain the positive effect of maternal employment on child obesity for highly educated mothers by differences in skills between mothers and caregivers in childcare settings. The educational attainment of the average caregiver in a childcare setting has been found to be slightly below college diploma (Early et al., 2007), meaning that it is lower than the only group for which we found adverse effects of non-parental childcare and higher than the groups for which we found favorable effects of non-parental childcare. It has been speculated that under the time constraints of professional employment, high-educated mothers might be less able to supervise their children's eating and exercise patterns (Anderson et al., 2003; Ruhm, 2008). Fertig et al. (2009) provides empirical evidence that the number of meals served by more educated mothers is inversely associated with children's obesity prevalence. They explain this by a decrease in the number of meals served at home leading to the substitution of more caloric restaurant meals. The latter finding by Fertig et al. (2009) fits the conceptual framework suggested by our theoretical model. The third term of the effect of childcare in our model consists of the effect of any change in goods inputs that the mother chooses because of working and consequently using childcare. This effect for high educated mothers could be substantial owing to sizable changes in the number of meals served at home due to employment.

We suggest that our finding of an opposite, favorable direction of the effect of using non-parental childcare may also in part be explained in part by differences in the education level of the mother and the childcare provider: in this case, the higher education levels of caregivers especially in center care relative to that of children whose mothers have less than or equal to 12 years schooling. Additionally,programs of center-based childcare that may involve indoor/outdoor activities and caloric intakes that are relatively more beneficial for child development compared to if those children of low-education mothers who received parent-only care. These may be especially important for children in low-income families whose neighborhood conditions are unfavorable to physical activity and high-quality nutrition (Powell et al. 2006, Dubowitz et al 2008). Supporting evidence of a favorable center-care effect is found for the Head Start program, which targets the children of low-income families. Head Start is the largest federally funded early-childhood program in the country, providing services to nearly one million low-income U.S. children, the majority of whom are racial/ethnic minorities (U.S. Department of Health and Human Services 2008a, 2008b). Childcare centers that have been accredited for Head Start are subject to stringent regulations and mandates relevant to prevention of childhood obesity (Story et al 2006). Worobey et al. (2005) provides evidence that children between 36 through 71 months old who participate in Head Start program consume fewer calories during the week than on the weekend when children spend most of their time with their parents. Randomized Control Trial interventions in Head Start facilities have been shown to improve nutrition (Williams et al 2004), reduce inactivity (Dennison et al 2004), and reduce obesity (Fitzgibbon et al 2005). Additionally, econometric studies using nationally-representative samples have found that participation in Head Start reduces the probability of becoming overweight or obese in later childhood among participants in the program, especially among Blacks (Frisvold 2006; Frisvold and Lumeng 2011). Care by relatives, however, has been found to be associated with higher obesity than center care (Benjamin et al 2009; Fertig et al 2009; Maher et al 2008), suggesting more detailed analysis by non-parental care type should be undertaken to better understand the sources of favorable effects of non-parental childcare among the children of low-education mothers.

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Table 1. Sample Selection

	# of children
Total children in CDS-PSID wave I	3563
The primary caregiver isn't biological mother	271
Born before 1987	690
Parents non-head of household	397
Working history of mother from birth to kindergarten is missing	55
Unknown state of residency	132
Missing maternal and household characteristics	207
Final Sample Size	**1941**

Table 2. Number of BMI measures per child in the final sample

# BMI measures	# children	# Obs.
0	86	0
1	327	327
2	871	1742
3	657	1971
Total	**1941**	**4040**

Table 3. Age distribution of BMI measures in the final sample

Age	Frequency	Percent	Cum.%
2	166	4.1	4.1
3	179	4.4	8.5
4	198	4.9	13.4
5	203	5.0	18.5
6	315	7.8	26.3
7	340	8.4	34.7
8	310	7.7	42.4
9	317	7.9	50.2
10	224	5.5	55.7
11	302	7.5	63.2
12	290	7.2	70.4
13	294	7.3	77.7
14	291	7.2	84.9
15	283	7.0	91.9
16+	328	8.1	100
Total	**4040**	**100**	

Table 4. Percentage of mothers who worked and who used non-parental child care by maternal education and child's age[1,2]

Education group	Age (in months)	Worked	Non-parental childcare
Below HS	3	18.3%	14.6%
(below 12 years)	24	22.1%	23.1%
	48	28.0%	26.7%
	60	29.5%	26.8%
HS diploma	3	35.5%	35.4%
(12 years)	24	45.1%	43.0%
	48	51.2%	42.1%
	60	52.3%	38.0%
Some College	3	37.8%	35.1%
(13-15 years)	24	49.0%	48.6%
	48	49.3%	45.0%
	60	51.4%	31.8%
Bachelors degree +	3	46.7%	40.9%
(16+ years)	24	55.1%	47.1%
	48	56.1%	43.7%
	60	52.7%	33.0%

[1]All statistics are computed using child level sample weights.
[2] In computing the above statistics, the final sample of 1,941children is used.

Table 5. Descriptive statistics for variables affecting child adiposity by child's obesity status[1,2]

		Non-obese		Obese	
		Mean	Std Dev	Mean	Std Dev
Mother married at birth		79.5%	40.4	70.6%	45.6
Maternal age at birth (in years)		27.0	5.3	26.5	5.6
Maternal education at birth					
	Below HS	14.5%	35.3	17.0%	37.5
	HS Diploma	33.0%	47.0	34.8%	47.6
	Some College	25.5%	43.6	32.1%	46.7
	College+	27.0%	44.4	16.2%	36.9
Maternal BMI ($lb*703/in^2$)		25.0	5.8	27.9	6.6
WIC during pregnancy		27.8%	44.8	34.4%	47.5
Food Stamps during pregnancy		13.4%	34.1	18.2%	38.6
Child's sex (Boy)		48.9%	50.0	60.2%	49.0
Child's race					
	White	71.1%	45.4	63.4%	48.2
	Black	12.9%	33.5	20.1%	40.1
	Hispanic	8.9%	28.5	12.0%	32.5
	Other	7.1%	25.7	4.4%	20.6
Birth weight (in pounds)		7.0	1.4	7.1	1.5
Born before due date		50.8%	60.6	57.2%	66.5
Log household income (in $1988 ('000))		4.8	1.0	4.6	1.0
Child's age (in years)		9.7	4.1	9.7	4.4
Non-parental childcare (in months)		22.6	24.0	24.7	23.6
Number of observations		3212		828	

[1] All statistics are computed using child level sample weights.

[2] In computing the above statistics, the final sample of 1,941children used.

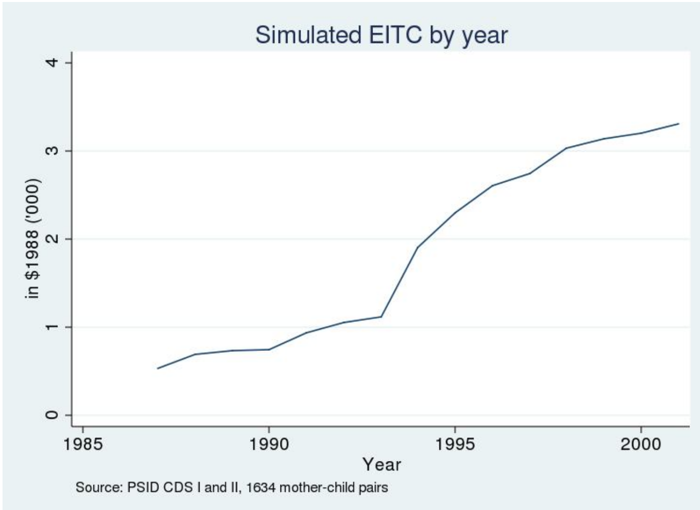

Figure 1. Simulated EITC by year

Table 6. Wald test of relevance and validness of exclusion restrictions [a]

Test	Description	Wald Test
Hypothesis 1[b] (Relevance)	Statistics	78.14
	Df	15
	p-value	**<0.0001**
Hypothesis 2[c] (Validness)	Statistics	4.37
	Df	5
	p-value	**0.497**

[a-]Wald statistics computed as $Wald = (R*\theta)'(R*COV*R)^{-1}(R*\theta)$ where R is a vector of constraints, θ is a vector of estimates and COV is a covariance-variance matrix.

[b-]H0: exclusion restrictions are jointly equal zero in work and childcare equations.

[c]-H0: exclusion restrictions are jointly equal zero in the obesity equation

Table 7. Joint model of maternal employment and childcare and child obesity with interacted maternal education and non-parental childcare experience (White-Huber standard errors)

	Obesity			Not working, non-parental care			Working, parental care			Working, non-parental care		
	Coeff.	z-stat.	p-value	Coeff.	z-stat.	p-value	Coeff.	z-stat.	p-value	Coeff.	z-stat.	p-value
Mother married at birth	-0.189	1.32	0.19	-0.053	0.38	0.71	0.473***	3.92	0.00	0.307***	2.23	0.03
Child sex(Boy)	0.233**	2.39	0.02	-0.088	0.83	0.41	-0.070	0.88	0.38	-0.158*	1.73	0.09
Maternal age at birth	0.008	0.88	0.38	-0.003	0.30	0.76	0.017*	1.68	0.10	0.016	1.54	0.13
Black	0.379***	2.78	0.01	0.189*	1.67	0.10	0.384***	3.88	0.00	0.119	0.87	0.39
Hispanic	0.442**	2.12	0.04	-0.005	0.03	0.97	0.162	0.94	0.35	-0.202	0.92	0.36
Other	-0.337	1.22	0.23	0.561***	3.55	0.00	-0.053	0.36	0.72	-0.637***	2.94	0.00
Below high school (<12)	1.070***	3.93	0.00	0.006	0.03	0.97	0.057	0.40	0.69	0.301*	1.83	0.07
High School (12)	0.890***	3.80	0.00	-0.170	1.54	0.13	0.055	0.47	0.64	-0.124	1.05	0.30
Some college (13-15)	0.765***	3.11	0.00	-0.150	1.02	0.31	-0.005	0.02	0.98	-0.222	0.82	0.42
Child's birth weight	0.114***	3.00	0.00	0.051*	1.71	0.09	0.004	0.13	0.90	0.027	0.92	0.36
Whether born before the due date	0.195**	2.19	0.03	0.204**	2.47	0.02	0.116	1.42	0.16	0.235***	2.87	0.00
Maternal BMI	0.062***	7.63	0.00	-0.004	0.53	0.60	-0.020***	3.00	0.00	-0.004	0.39	0.70
During pregnancy in WIC	-0.081	0.56	0.58	-0.0004	0.004	1.00	-0.086	0.48	0.63	-0.150	0.58	0.56
During pregnancy in Food Stamp	-0.234	1.56	0.12	0.124	0.74	0.46	-0.080	0.59	0.55	-0.338*	1.81	0.07
Work experience after child birth				-0.033***	4.83	0.00	0.048***	12.05	0.00	0.011*	1.86	0.07
Non-parental childcare(EXPC)	0.010*	1.64	0.10	0.115***	22.88	0.00	-0.009**	2.06	0.04	0.109***	21.91	0.00
Below high school (<12)*EXPC	-0.018**	2.42	0.02									
High School (12)*EXPC	-0.020***	3.10	0.00									
Some college (13-15)*EXPC	-0.009	1.41	0.16									
EITC benefits				0.038	0.58	0.57	-0.016	0.29	0.77	0.090	1.53	0.13
EITC benefits*mother married				0.0001	0.001	1.00	-0.167**	2.15	0.03	-0.293**	1.95	0.05
Average wage in a state				-0.016	0.61	0.54	0.017	1.21	0.23	-0.051***	2.85	0.01
Average unemployment rate in a state				-0.039	0.81	0.42	-0.145***	4.62	0.00	0.024	0.64	0.52
% of people working in service in a state				-0.024*	1.92	0.06	-0.067***	7.15	0.00	-0.022*	1.85	0.07
Time				-0.059***	12.12	0.00	0.002	0.55	0.59	-0.069***	12.88	0.00
Constant	-5.146***	8.51	0.00	-2.979***	3.73	0.00	-2.731***	5.38	0.00	-7.087***	4.80	0.00
Unobserved Heterogeneity mass point 2	0.090	0.50	0.62	1.637***	3.47	0.00	3.550***	18.14	0.00	5.527***	3.86	0.00
Unobserved Heterogeneity mass point 3	0.470*	1.90	0.06	3.962***	12.23	0.00	1.652***	3.98	0.00	4.881***	3.44	0.00
Unobserved Heterogeneity mass point 4	0.138	0.67	0.50	4.247***	10.88	0.00	5.740***	25.70	0.00	8.371***	5.81	0.00
Unobserved Heterogeneity mass point 5	0.448*	1.90	0.06	4.425***	12.31	0.00	3.279***	15.03	0.00	8.563***	6.09	0.00
Unobserved Heterogeneity mass point 6	0.431*	1.81	0.07	3.988***	9.25	0.00	5.163***	20.75	0.00	10.696***	7.66	0.00
# of observations	1855			121616			121616			121616		

* - statistically significant at the 0.10 level,** - statistically significant at the 0.05 level,*** - statistically significant at the 0.01 level.
Unobserved heterogeneity mass point 1 is normalized to 0 in each equation. Estimated weigts are Pr2=0.16*, Pr2=0.11***,Pr3=0.13***,Pr4=0.22*,Pr5=0.19, Pr1=1-(Pr2-Pr3-Pr4-Pr5-Pr6)=0.19.
In the obesity equation also is included child's age at assessment and cumulative household income. Both parameters are highly insignificant.

Table 8. Comparison of simulated and observed probability of child obesity, work and childcare experience in months (goodness-of-fit test)

	Observed			Simulated			p-value
	# obs.	Mean	Std Dev	# obs.	Mean	Std Dev	
Obesity	4040	0.205	0.404	100	0.204	0.015	0.980
Work Experience	1941	30.518	24.542	100	30.328	0.493	0.938
Childcare Experience	1941	24.087	24.122	100	24.694	0.596	0.801

Note: Simulation of main outcomes is performed with 100 random draws from a multivariate normal distribution centered at the estimated values of the parameters with covariance matrix equal to the estimated covariance matrix

Table 9. Simulated probability of child obesity by education and child care experience

Childcare	Less than 12 years		12 years		13-15 years		16+ years	
in months	Mean(Std)	Δ [1]	Mean	Δ [1]	Mean	Δ [1]	Mean	Δ [1]
0	0.276(0.032)		0.245(0.023)		0.228(0.024)		0.131(0.024)	
12	0.258(0.024)	-0.018***	0.227(0.017)	-0.018***	0.230(0.020)	0.002	0.145(0.021)	0.014***
24	0.241(0.022)	-0.017***	0.211(0.016)	-0.016***	0.232(0.020)	0.002	0.160(0.020)	0.015***
36	0.226(0.026)	-0.016***	0.195(0.018)	-0.016***	0.234(0.025)	0.003	0.176(0.023)	0.016***
48	0.211(0.033)	-0.014***	0.181(0.022)	-0.014***	0.237(0.033)	0.003	0.194(0.029)	0.017***
60	0.198(0.041)	-0.013**	0.167(0.026)	-0.014***	0.240(0.042)	0.003	0.212(0.038)	0.019***

Note: Simulation of main outcomes is performed with 100 random draws from a multivariate normal distribution centered at the estimated values of the parameters with covariance matrix equal to the estimated covariance matrix

* - statistically significant at the level of 10%,** - statistically significant at the level of 5%,*** - statistically significant at the level of 1 %

[1]- Δ measures the difference between simulated probability for cumulative childcare experience for n and n+12 months. For example, for the average mother with less than 12 years of education, an increase in childcare experience from 0 months to 12 months results in a 0.258-0.276=0.018 or 1.8% decrease in the probability of child obesity.

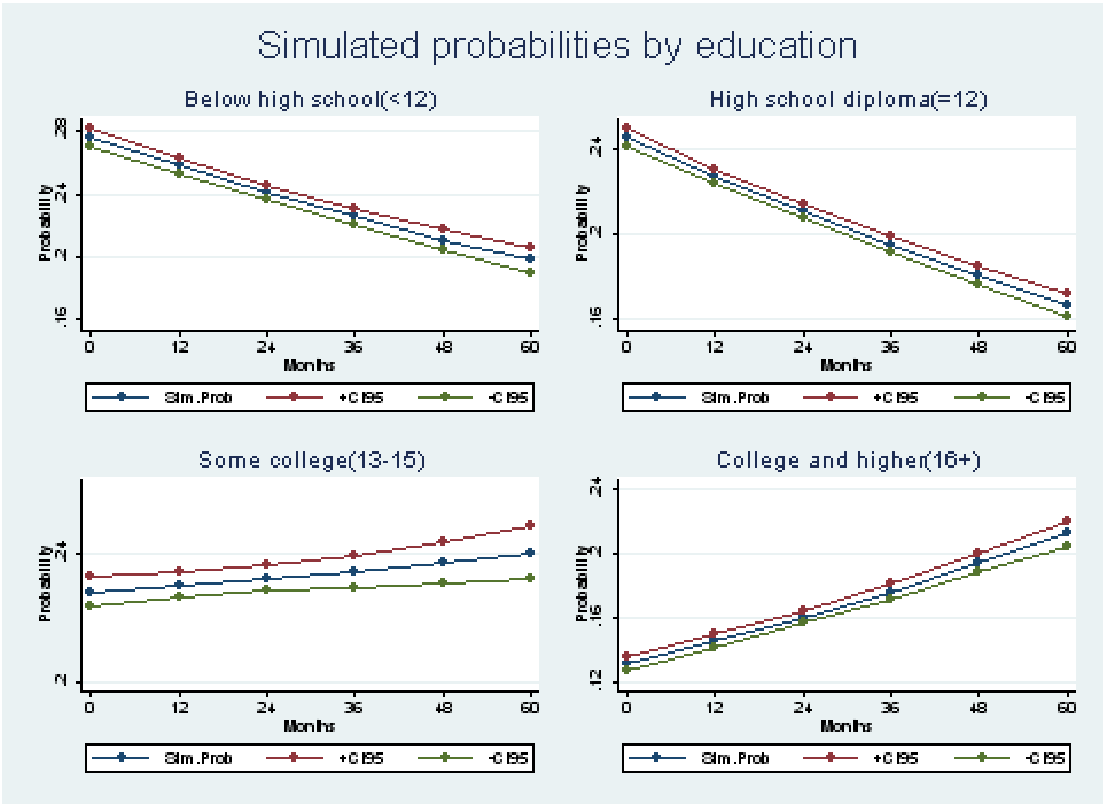

Figure 2. Simulated probabilities of obesity by maternal education

Table 10. Child obesity equation without controlling for unobserved heterogeneity (logit)

	Coeff.	z-stat.	p-value
Married at birth	-0.188	1.31	0.20
Child sex(Boy)	0.223**	2.28	0.03
Maternal age at birth	0.008	0.79	0.44
Black	0.388***	2.84	0.01
Hispanic	0.441**	2.14	0.04
Other	-0.352	1.27	0.22
Below high school (<12)	1.019***	3.82	0.00
High School (12)	0.890***	3.85	0.00
Some college (13-15)	0.768***	3.16	0.00
Child's birth weight	0.113***	2.96	0.01
Whether born before the due date	0.188**	2.12	0.05
Maternal BMI	0.061***	7.66	0.00
During pregnancy in WIC	-0.082	0.57	0.58
During pregnancy in Food Stamp	-0.231	1.55	0.14
Formal child care experience(EXPC)	0.016***	3.00	0.01
Below high school (<12)*EXPC	-0.017**	2.33	0.03
High School (12)*EXPC	-0.019***	3.13	0.01
Some college (13-15)*EXPC	-0.009	1.41	0.17
Child's age at assessment	-0.001	0.82	0.42
Cumulative household income	0.002	0.03	0.98
Constant	-4.892***	8.44	0.00
# of observations	1855		

Statistically significant at the 0.10 level, ** - statistically significant at the 0.05 level, *** - statistically significant at the 0.01 level.

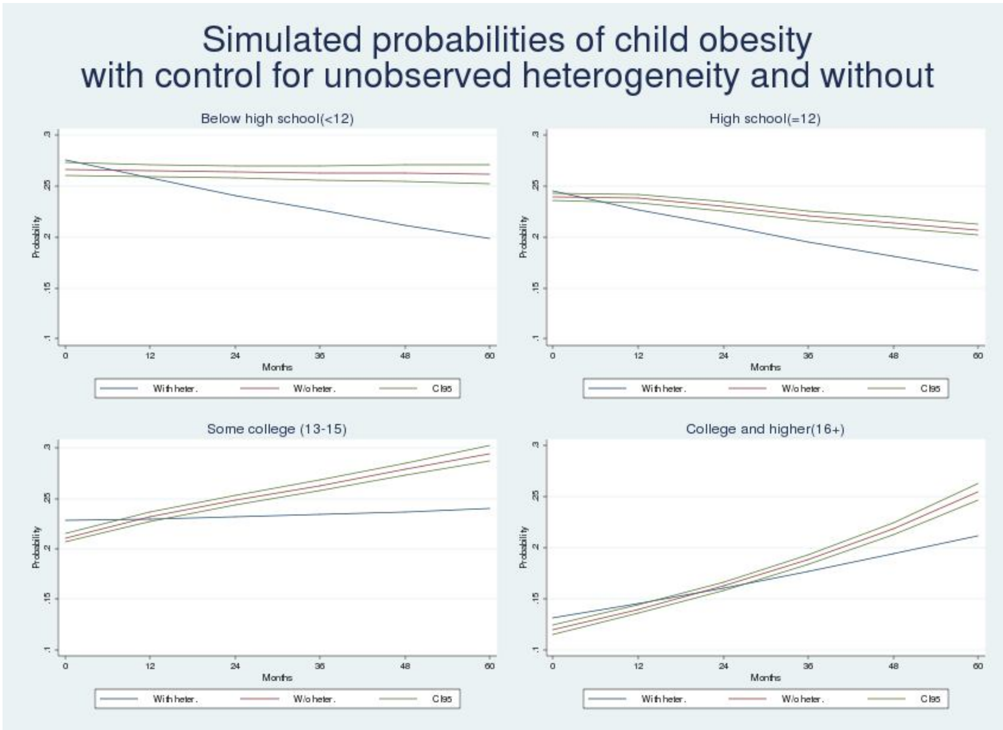

Figure 3. Comparison of simulated probabilities for child obesity between models with and without controlling for unobserved heterogeneity

APPENDIX.

Maternal employment variable construction

For each mother the monthly employment history was constructed using multiple sets of employment related questions asked from both head of the family unit and his wife. In each wave of the PSID the respondent was asked about his/her current employment status. If the status was “working now”, then the respondent was asked the question about the employment status for each month of the previous year separately. If the respondent wasn’t employed, then he/she was asked in which months during the previous year he/she was working. This allowed us to construct the monthly employment history for most respondents for years 1987-1996, 1998, and 2000. Because the PSID became a biennial survey after 1997, the monthly employment history was incomplete for years 1997 and 1999. To fill this gap, we used question that asked in what month and year the respondent started working for his/her present employer in waves 1999 and 2001. Furthermore, we used the current employment status of the respondent for waves 1997 and 1999.

For some respondents the employment history was incomplete due to non-responses, to fill gaps in the employment history we also used the question which asked about the month and year when the respondent started working for the current employer in each wave and if the respondent wasn’t employed in a given wave, then in what month and year he/she last worked. The final source of information about the employment history of the respondent came from the question which clarified whether he/she had ever done any work for money in the past.

Table A1. Earned Income Tax Credit Parameters, 1996-2003 (in nominal dollars)

Year	# of depend.	Phase-in Rate %	Phase-in Range ($)	Max Credit ($)	Phaseout Rate(%)	Phaseout Range($)
1987	>=1	14	0-6,080	851	10	6,920-15,432
1988	>=1	14	0-6,240	874	10	9,850-18,576
1989	>=1	14	0-6,500	910	10	10,240-19,340
1990	>=1	14	0-6,810	953	10	10,730-20,264
1991	>1	16.7	0-7,140	1,192	11.93	11,250-21,250
	0	17.3		1,235	12.36	
1992	>=1	17.6	0-7,520	1,324	12.57	11,840-22,370
	0	18.4		1,384	13.14	
1993	>=1	18.5	0-7,750	1,434	13.21	12,200-23,050
	0	19.5		1,511	13.93	
1994	1	23.6	0-7,750	2,038	15.98	11,000-23,755
	>1	30	0-8,245	2,528	17.68	11,000-25,296
	0	7.65	0-4,000	306	7.65	5,000-9,000
1995	1	34	0-6,160	2,094	15.98	11,290-24,396
	>1	40	0-8,640	3,110	20.22	11,290-26,673
	0	7.65	0-4,100	314	7.65	5,130-9,230
1996	1	34	0-6,330	2,152	15.98	11,610-25,078
	>1	40	0-8,890	3,556	21.06	11,610-28,495
	0	7.65	0-4,220	323	7.65	5,280-9,500
1997	1	34	0-6,500	2,210	15.98	11,930-25,750
	>1	40	0-9,140	3,656	21.06	11,930-29,290
	0	7.65	0-4,340	332	7.65	5,430-9,770
1998	1	34	0-6,680	2,271	15.98	12,260-26,473
	>1	40	0-9,390	3,756	21.06	12,260-30,095
	0	7.65	0-4,460	341	7.65	5,570-10,030
1999	1	34	0-6,800	2,312	15.98	12,460-26,928
	>1	40	0-9,540	3,816	21.06	12,460-30,580
	0	7.65	0-4,530	347	7.65	5,670-10,200
2000	1	34	0-6,920	2,353	15.98	12,690-27,413
	>1	40	0-9,720	3,888	21.06	12,690-31,152
	0	7.65	0-4,610	353	7.65	5,770-10,380
2001	1	34	0-7,140	2,428	15.98	13,090-28,281
	>1	40	0-10,020	4,008	21.06	13,090-32,131
	0	7.65	0-4,760	364	7.65	5,950-10,708

Source: 1988-2001 parameters come from Hotz and Scholz (2003)

Table A2. State Earned Income Tax Credits (before 2001)

Type of credit	Year adopted	State	% of Federal Credit
Refundable Credits	1999	Colorado	10
	2000	DC	25
	1998	Kansas	10
	1987	Maryland	16
	1997	Massachusetts	15
	1991	Minnesota	33
	2000	New Jersey	15
	1994	New York	25
	1988	Vermont	32
	1989	Wisconsin	4 one child, 14 2 children, 43 3 children and more
Nonrefundable Credits	2000	Illinois	5
	1990	Iowa	6.5
	2000	Maine	5
	1997	Oregon	5
	1975	Rhode Island	25.5

Source:Holtz and Scholz (2003)