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MOTHER'S EMPLOYMENT, CHILD CARE USE AND COGNITIVE DEVELOPMENT IN EARLY CHILDHOOD [1]

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ABSTRACT

This paper aims to analyze the effects of mother's employment and non-parental child care on cognitive development in early childhood. Investment in the development of children at early rather than later ages provides higher returns in terms of labor market outcomes. Thus, decision making process of primary care givers are extremely important at this period. A nationally representative longitudinal data for the United States of America is used in this paper. Hybrid production function for the cognitive development is estimated within a dynamic framework using a two-step system Generalized Method of Moments estimator. The results show that more hours of center-based care significantly increase cognitive achievement and this holds true when center-based care is defined as full- or part-time. Furthermore, both a high quality home environment and a high quality out-of-home child care improve a child's cognitive development while there is no statistically significant impact of maternal work hours.

Keywords: *Child Care, Cognitive Development, Generalized Method of Moments*

JEL Codes: *C23, I21, J13*

ANNENİN İSTİHDAMI, ÇOCUK BAKIMI KULLANIMI VE ERKEN ÇOCUKLUK DÖNEMİNDE BİLİŞSEL GELİŞİM

ÖZET

Bu çalışma annenin istihdamının ve çoçuk bakımı kullanımının erken çocukluk döneminde bilişsel gelişim üzerindeki etkilerini analiz etmeyi amaçlar. Çocukların gelişimine geç yaşta degil erken yaşta yatırım yapmak daha yüksek emek piyasası getirileri sağlar. Bu yüzden öncelikli bakım sağlayıcıların bu dönemde karar verme süreci oldukça önemlidir. Bu çalışmada Amerika Birleşik Devletleri için ulusal temsili bir panel veri kullanılır. İki aşamalı sistem Genelleştirilmiş Beklemler Yöntemi tahmincisi kullanılarak dinamik bir çerçevede bilişsel gelişim için hibrit üretim fonksiyonu tahmin edilir. Sonuçlar daha fazla saat kreş kullanımının bilişsel gelişimi anlamlı olarak etkilediğini ve bunun kreş kullanımı tam ya da yarı zamanlı olarak tanımlandığında da geçerli olduğunu gösterir. Ayrıca, annenin çalışma

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saati istatistiksel olarak anlamlı değilken yüksek kalite ev ortamı ve ev dışı çocuk bakımının her ikisi de çocukların bilişsel gelişimini geliştirir.

Anahtar Kelimeler: *Çocuk Bakımı, Bilişsel Gelişim, Genelleştirilmiş Beklemler Yöntemi*

JEL Kodları: *C23, I21, J13*

1. INTRODUCTION

The purpose of this research is to analyze the effects of maternal employment and non-parental child care on the cognitive development of children during early childhood using the quality of the home environment and quality of child care as inputs in the production process. Because a child's cognitive development is more strongly affected by parental inputs at early rather than later ages and these early achievements predict later educational and labor market outcomes, it is important to invest in the cognitive development of children as early as possible (Carneiro and Heckman, 2003; Cunha and Heckman, 2008; Currie and Thomas, 1999; Heckman and Mosso, 2014). In addition, both cognitive skills and non-cognitive traits such as emotions, personality, social interaction, attention and concentration impact economic outcomes, e.g., schooling, wages and earnings (Heckman, Stixrud and Urzua, 2006; Lindqvist and Vestman, 2011; Eren and Ozbeklik, 2013). Since parents and child care providers play an influential role in the early stages of a child's life, understanding how parental time and non-parental child care affect a child's cognitive development in early childhood is extremely important. The literature on child care and child outcomes is dominated by studies on maternal child care and employment and there has been very little focus on paternal child care and employment. This is likely due to the fact that between 1975 and 2008, labor force participation rates of mothers with children under age 6 (ages 6 to 17) rose from 39% to 63.6% (54.9% to 77.5%).[2] This large increase in labor force participation rates by mothers has raised questions about the impact of maternal employment on child outcomes as well as the importance of non-parental child care. Although fathers contribute to child rearing, most mothers bear the majority of the burden apart from non-parental child care providers. As shown by Cawley and Liu (2012), fathers contribute only a small percentage of time to housework and child-rearing activities when mothers are working outside the home.

Possible mechanisms by which maternal employment positively affects child development are through an increase in family income, improved self-esteem of the mother, information gained from coworkers, and employer provided child care subsidies. On the other hand, working mothers have less time to spend on house work, child rearing and food preparation, as shown in time-use studies (Bianchi, Milkie, Sayer and Robinson, 2000; Cawley and Liu, 2012; Nock and Kingston 1988). Having less time available for activities with children may negatively influence their cognitive development. Thus, the

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[2] Bureau of Labor Statistics, U.S. Department of Labor, *The Editor's Desk*, Labor force participation rates among mothers. http://www.bls.gov/opub/ted/2010/ted_20100507.htm.

quality of a mother's time with her child should be taken into account in order to improve our understanding of how important maternal time is for child development. Non-parental child care arrangements are very important for working mothers since not only do they provide a learning environment to stimulate cognitive development when they are in care but they also provide nutrition and physical activities for children which affect their physical health. However, it is imperative to control for the quality of child care when analyzing its impact on child outcomes since child care arrangements differ markedly in quality measures such as group size and frequency of activities in child care settings.

There are three main issues in the literature regarding maternal employment, child care and child development. First, employment and child care decisions are not examined as joint decisions in most studies. Working mothers typically use some amount of child care when they are not available to care for their children, so analyzing the impact of only one will confound the effect of other. Thus, it is important to look at the effects of both decisions jointly instead of analyzing the impact of only a single variable. Second, there may be an omitted variable bias problem resulting from ignoring quality variables, home quality and child care quality, and the unobserved inputs (to the researcher). Net household income and determinants of unobserved inputs should be controlled to the extent that bias might be caused by unobserved inputs. Some models from existing literature include quality measures, but they are treated as exogenous. Moreover, most of them ignore unobserved inputs such as medical care, nutrition, and quality of child care or include only total household income. In addition to unobserved inputs, such as quality, there may be permanent and/or time-varying unobservable (to the researcher) child and/or mother characteristics that are correlated with both the mother's choice variables and the child's outcome variables. Most past studies either include too many child-family controls, which are potentially endogenous, or employ only fixed effects (FE) models. However, if there are time-varying unobservables that affect both choice variables studied and child outcomes, FE results may still not estimate a causal model.

All of these aforementioned points will be considered in this research in order to analyze the impact of maternal employment and child care on child cognitive development. This research estimates cognitive achievement production function within a dynamic framework using a nationally representative data set, Early Childhood Longitudinal Study-Birth Cohort (ECLS-B). One of the contributions of this study to the literature is an estimate of the effects of maternal employment and child care decisions together by including home quality and child care quality measures derived from information on child nutrition, parenting style, and home and child care environments in the ECLS-B data set. The production functions are estimated using a two-step system GMM estimator to control for unobserved heterogeneity. Since all inputs are not observed, the determinants of unobserved inputs are controlled for in the production functions. The results suggest that a high quality home environment has the potential to yield important benefits by improving children's cognitive achievement. In addition, high quality out-of-home child care improves cognitive development. Center-based child care is shown to be beneficial for cognitive development. Those results imply that significant impacts of maternal work and child care on cognitive outcome might be misleading and incomplete since some or all of these factors were either omitted or their endogeneity was not properly modeled in past studies.

Section 2 presents relevant literature on maternal employment, child care and child cognitive outcome. Section 3 describes the data. The estimation procedure is explained in Section 4 and estimation results are shown in Section 5. Finally, Section 6 concludes.

2. LITERATURE REVIEW

While there is extensive literature that focuses on the effect of maternal employment and/or child care use on children's cognitive development, only a few studies deal with the endogeneity of those decisions. Therefore, the results of these studies may not be causal effects.[3] Bernal (2008), Bernal and Keane (2010) and Bernal and Keane (2011) find that child care decreases cognitive achievement of children, controlling for the endogeneity of child care, while Bernal and Keane (2011) show that informal child care negatively affects the cognitive development of children of single mothers but formal care (i.e,. center-based) does not.[4] On the other hand, Herbst (2013) shows that children from advantaged families have lower cognitive achievement if they receive non-parental care (especially center-based) than peers in parental care and that there is no benefit for disadvantaged children. This is shown by using the seasonality in the timing of the survey for the first two waves of ECLS-B as a source of exogenous variation in the attendance to non-parental child care. However, he does not control for the cognitive score from the previous period or include quality variables in the cognitive achievement regression although he argues that the instrument is not related to quality.[5] Child care settings show

[3] Bernal and Keane (2011) provide a comprehensive literature on maternal employment and/or child care use on child cognitive development. Many studies use OLS by controlling for a large number of variables, some of which are potentially endogenous (NICHD, 2000; Ruhm, 2004; NICHD and Duncan, 2003), or use mother fixed effects which do not control for the omitted time-varying unobservable heterogeneity/inputs correlated with both the child's cognitive development and child care arrangements (Blau, 1999).

[4] Bernal and Keane (2011) use 78 instruments constructed from 1996 welfare reform and earlier policy changes. The instrument list is constructed from policies such as federal waivers received from 1993 to 1996, and changes after the 1996 federal Personal Responsibility and Work Opportunity Reconciliation Act (PRWORA). The estimation methods that they use include OLS, two-stage least squares (2SLS), generalized method of moments (GMM), Fuller, and limited information maximum likelihood (LIML). Factor analysis is also used in order to reduce the number of instruments. Then results are compared using the 78 instruments and estimated factor scores from factor analysis on the list of instruments. However, the author generates child care time by looking at a mother's employment status since they do not have actual data on non-parental child care time. Therefore, even if their instruments are highly correlated with the constructed child care variable, it is difficult to separate the impact of child care use from that of maternal time.

[5] However, quality measures are available only at Wave 2, so there may still be unobserved quality effects. Even if the coefficient of the instrument is not significant in quality equations (except for five cases), Herbst (2013) finds consistently

considerable heterogeneity with respect to the quality of infrastructure and education. Thus, any finding regarding the child care effect may be resulted from the choice of a particular child care quality type by families. Even if non-parental child care results in worse outcomes during earlier years (based on his results from the first two waves of the data), since in this paper all waves are included, the finding of positive impact of non-parental child care may reflect that children benefit from non-parental child care as they get older. More recently, Kühnle and Oberfichtner (2017) study the effect of attending child care early on children's cognitive and non-cognitive development. Their results show no statistically significant difference in terms of standardized cognitive test scores and they do not estimate the impact of quality on the outcomes. Carta and Rizzica (2018) do not find significant impact of early access to subsidized child care on children's cognitive outcomes (math and language test scores) using data from Italy. However, impact of child care quality is not covered. Felfe and Lalive (2018) examine the early child care attendance on child development outcomes including language skills by exploiting an early child care reform in Germany. Results show only a weak impact of child care on language skills. They, however, do not estimate the effects of child care quality but instead quality of care centers at the aggregate level are compared between fast- and slow-expansion districts.

Besides the findings mentioned above, it has been shown that there are benefits from attending high-quality child care settings (Abner, Gordon, Kaestner and Korenman, 2013; Peisner-Feinberg, Burchinal, Clifford, Culkin, Howes, Kagan and Yazejian, 2001; Hill, Waldfogel and Brooks-Gunn, 2002; NICHD and Duncan, 2003).[6] While the OLS and mother fixed effects results from Blau (1999) exhibit wrong signs, especially for the child-staff ratio and training variables, he finds small but significant effects of small group size on the cognitive development of children.[7] Duncan and NICHD (2003) demonstrate positive effects of high quality child care on children's cognitive development by estimating value-added models. However, this does not solve the endogeneity problem arising from the potential correlation between unobservables and inputs. Griffen (2018) estimates a value-added specification of a cognitive achievement production including home and child care quality from ECLS-

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negative effects i.e., most measures of quality of child care seem to be lower during summer. Moreover, there is no clear explanation about the possible reasons for the negative impact on advantaged children. His argument that child care subsidies lead to worse outcomes for children is due to the center-based setting, where most subsidized children are placed, may not be complete since it is also argued that families using a subsidy may choose lower quality care. Thus, there might be a quality effect of child care on child outcomes. It would be useful to check for the robustness of his results by including child care quality in the regressions for cognitive achievement while controlling for endogeneity.

[6] Peisner-Feinberg et al. (2001) and Hill et al. (2002) investigate the impact of quality in center-based settings. Peisner-Feinberg et al. (2001) uses set of controls with OLS whereas Hill et al. (2002) uses a randomized study. Abner et al. (2013) estimate weighted least squares with a set of controls for children having data on quality. That is, their analysis include only children receiving child care.

[7] However, as he points out irregular measurement of child care variables in the National Longitudinal Survey of Youth 1979 (NLSY79) makes analysis difficult. In addition, he states that the nature of the data and diversity of methods used for the analysis of child care inputs strongly affect the results.

B in a dynamic discrete choice framework in order to examine the effects of child care policies: Head Start and child care subsidies while the impacts of those types of programs are not covered in this paper.

3. DATA AND DESCRIPTIVE STATISTICS

The primary data used in this research are from a nationally representative restricted-use data set, the ECLS-B. This is a longitudinal study that followed a sample of approximately 14,000 children born in 2001 from birth through kindergarten entry. The ECLS-B contains information about children, their families, early education, and child care providers and teachers across the United States. Five rounds of data were collected that occurred when the children were approximately 9 months old (2001-02), 2 years (2003-04), 4 years /preschool age (2005-06) and in the fall of 2006. In 2006, approximately 75% of children were in kindergarten or higher. Thus, in the fall of 2007, the remaining 25% of the children who had not entered kindergarten or higher previously, as well as children who were repeating kindergarten were interviewed again. Data from all five waves are utilized in this paper.

In every data collection round, the parent respondent (usually the mother) was asked about the parents' employment, earnings, family background, child care arrangements and the child's health. Starting when the children were 2 years old, their child care and early education providers were interviewed and asked about their child care activities with the children. ECLS-B data contains the Bayley Short Form- Research Edition (BSF-R) at Waves 1 and 2. In this paper, scale mental scores are used as cognitive achievement measures for the children at Waves 1 and 2. For other waves, both scale and T-scores for math and reading tests are available. The average of the scaled version of the math and reading scores measured at Waves 3, 4 and 5 are included. These tests were adapted from widely known early reading and math assessments such as the Peabody Picture Vocabulary Test- Third Edition (PPVT-III), the Test of Early Mathematics Ability-3 (TEMA-3), the Preschool Comprehensive Test of Phonological and Print Processing (Pre-CTOPPP), the PreLAS 2000 and questions from the Early Childhood Longitudinal Study-Kindergarten (ECLS-K). All scale measures are then standardized in order to construct a longitudinal measure of cognitive achievement.

A mother's choice variables are hours worked last week, home quality, hours of child care for each type (home-based child care and center-based child care), quality of primary child care, mother's current marital status, number of siblings of the focal child, and the mother's education level, defined as whether the mother has a university degree or not.[8] Exogenous family/child characteristics are the child's age, child's gender, child's race and ethnicity, mother's age, whether the family lives in an urban or rural area, region of residence and the income of the partner. Two main non-parental child care quality measures are created for this paper. Group size is a structural child care quality measure reported by the parent and is the number of children in a child care setting. The variable is available for all three types

[8] Home-based child care includes both relative care and nonrelative care.

of non-parental child care and all waves. If a family uses more than one type of child care, average group size is used.[9] Process quality is the second non-parental child care quality variable that measures the interaction between the child and his/her primary child care provider. Process quality includes the frequency with which the primary child care provider reads, does math, and plays music with the child. It also includes items representing the child care environment such as the number of books and toys available and whether the child care arrangement has a reading area or not. [10] Since a primary child care arrangement can take place in a child's own home, two child care quality measures are defined, which are in-home primary child care quality and out-of-home primary child care quality. [11] All primary center-based child care arrangements are defined as out-of-home child care. Since it is not feasible to include every variable separately in the production functions, a quality index is created from the estimated first principal component from factor analysis. This method allows us to combine multiple variables into a single index.[12]

The home quality index is also created by using factor analysis that combines information about the materials available in a child's home, nutrition of the child and the mother's interaction with the child into a single index. For example, the number of books and toys, type of beverage that the child drinks with meals, how often the mother tells stories to child, and takes the child to a library are some examples of the variables that are used in the factor analysis to create a home quality index. However, some of the variables used to construct a quality measure for non-parental child care at home are

[9] The percentage of families who use multiple child care arrangements in my sample are 1.9%, 2.7%, 20% and 20% for Waves 1, 2, 3 and 4 respectively.

[10] The definition of primary childcare from the ECLS-B user's manual: "The *primary* child care provider is the person who provides the most care to the child in the regular non-parental caregiving arrangement where the child spends the most number of hours per week in care. If the child spends the exact same number of hours with different care providers in the 2nd wave, one provider was selected at random to be the primary child care provider. If the number of hours was the same for two or more types of care in the 3rd wave, then selection of an arrangement for the ECEP (Early Care Education Provider) was made with the following order of preference: Head Start, relative care, nonrelative care, and non-Head Start centers. For cases in which a child spent the exact same number of hours per week with different care providers in the 4th wave, one provider was selected to be the subject of the ECEP, based on the type of care arrangement, in the following order of preference: Head Start program, other center-based care, home-based care (relative), and home-based care (nonrelative). For cases in which a child spent the exact same number of hours per week with different care providers in the 4th wave, the provider was selected to be the subject of the WECEP (Wrap-around Education and Early Care Provider) interview, based on type of care, in the following order of preference: center-based care, home-based care (relative), and home-based care (nonrelative)."

[11] The variables that are used to construct the quality index for the primary child care arrangement are in the PhD thesis and available upon request.

[12] As mentioned in Griffen (2018), although ECERS is a widely used quality measure for child care quality, it is available for a small subset of children in ECLS-B. In addition, the HOME scale in ECLS-B, which is a measure for home quality, includes only a subset of questions from the original version of this scale. Therefore, factor analysis is also used to create the quality variables.

equivalent to the variables related to home quality. Thus, if there are questions asked of both the respondent parent and primary caregiver at home, the information given by the parent is used.[13]

Since ECLS-B oversamples twins, one child from each twin pair is randomly selected and the other is excluded from estimation. Column 1 in Table 1 shows the number of observations at each wave and the second column shows the sample size after one child from each twin pair is selected. Table 2 shows the averages of cognitive achievement index by the level of the left hand side variables. Average cognitive achievement is higher for children whose mothers worked part-time, and used either full-time center-based care or part-time home-based care.

Table 1. Sample size

	Sample size	Sample size after twin restriction
Wave1	10700	9900
Wave2	9850	9050
Wave3	8950	8250
Wave4	7000	6450
Wave5	1900	1700

Notes: Sample sizes (N) are rounded to the nearest 50 as required by NCES.

Table 2. Cognitive Outcome by Employment and Child Care Variables

	Cognitive Achievement
Full-time work	0.119
	(0.987)
Part-time work	0.142
	(0.982)
Full-time center-based child care	0.234
	(0.969)
Part-time center-based child care	0.202
	(0.983)
Full-time home-based child care	0.037
	(1.006)
Part-time home-based child care	0.077
	(0.987)
N	20850

Notes: Sample sizes are rounded to the nearest 50 as required by NCES. Standard deviations in parentheses. Full-time: >35 hours, Part-time: > 0 & ≤ 35 hours.

[13] The variables used in the factor analysis for home quality is in the PhD thesis and available upon request.

4. EMPIRICAL MODEL

A hybrid production function for the cognitive achievement level of the child is given in equation (1) as below:

$$Q_{it} = \alpha_0 + \alpha_1 H_{it-1} + \alpha_2 Q_{it-1} + \alpha_3 B_{it-1} + \alpha_4 R_{it-1} + \alpha_5 X_{it-1} + \alpha_6 Z_{t-1} + \mu_i^Q + \varepsilon_{it}^Q \quad (1)$$

where μ_i^Q is unobserved time-invariant heterogeneity and ε_{it}^Q is the idiosyncratic error term. As can be seen in equation (1), child's cognitive outcome variable (Q) at the beginning of the period is assumed to depend upon the cognitive outcome from the previous period, health[14] (H) and non-cognitive[15] (B) skill of the child from the previous period, a vector (R) including the mother's choices (hours of work, child care use, child care quality and home quality, marital status, education level, number of child's siblings), health shock that a child can receive such as ear infections and respiratory illnesses and the income variable from the previous period and exogenous demographic variables (X). Since not all goods and time inputs are available in the data, state/county-level determinants of unobserved inputs such as medical care and nutrition intake from the previous period are also included (Z).

Estimation of equation (1) by OLS will not provide consistent estimates of the parameters since by construction the previous output is correlated with time-invariant heterogeneity μ_i^Q. Taking first difference of equation (1) will remove μ_i^Q as shown below.

$$Q_{it} = \alpha_1 \Delta H_{it-1} + \alpha_2 \Delta Q_{it-1} + \alpha_3 \Delta B_{it-1} + \alpha_4 \Delta R_{it-1} + \alpha_5 \Delta X_{it-1} + \alpha_6 \Delta Z_{t-1} + \Delta\varepsilon_{it}^Q \quad (2)$$

However, the first difference of the outcome, for instance ΔQ_{it-1}, is correlated with $\Delta\varepsilon_{it}^Q$ by construction as are the first differences of the other outcome variables. Therefore, based on the work by Arellano and Bover (1995), Blundell and Bond (1998) proposed a system GMM estimation method in which equations (1) and (2) are jointly estimated using moment conditions of lagged differences as instruments for the level equation in addition to moment conditions of lagged levels as instruments for the first difference equation. This system estimator is more efficient than estimating only one of those equations (Blundell and Bond, 1998). The other lagged variables included in the vector R in the production function are assumed to be endogenous since both a mother and her child's unobserved time-invariant characteristics may be correlated with these lagged variables. Therefore, we need instruments for these variables in the level equations. Moreover, these variables are also likely to be correlated with

[14] It is the obesity status of the child. The theoretical logic behind this production function is explained in the PhD thesis and available upon request.

[15] The non-cognitive skills cover a large range of skills such as internalizing behaviors (i.e., negative behaviors towards himself/herself such as being unhappy) and externalizing behaviors (i.e., behaviors towards other people such as aggressiveness), communication skills, attention and memory. The details are in the PhD thesis and available upon request.

the time-varying error term in equation (2). Thus, we also need instruments for these variables in the first difference equation (2).

As it is seen from (2), for example, $\Delta Q_{it-1} = Q_{it-1} - Q_{it-2}$ is correlated with $\Delta\varepsilon_{it}^{Q} = \varepsilon_{it}^{Q} - \varepsilon_{it-1}^{Q}$ since Q_{it-1} is correlated with ε_{it-1}^{Q}. Note that Q_{it-2} is correlated with ΔQ_{it-1} but orthogonal to $\Delta\varepsilon_{it}^{Q}$ if the errors are serially uncorrelated. Because of this Q_{it-2} can be used as an instrument for ΔQ_{it-1} equation (2). Additional moment conditions rely on the assumption that idiosyncratic error terms are serially uncorrelated. Thus, equation (2) implies that starting from time t=3, the idiosyncratic error terms are uncorrelated with the outcome variable at least two previous periods as below:

$$[Q'_{it-k}\Delta\varepsilon_{it}^{Q}] = 0 \quad \text{for t>=3 and all 2<=k<=t-1}$$

Therefore, valid instruments for example are Q_{i1} for t=3, $\{Q_{i1}, Q_{i2}\}$ for t=4 and $\{Q_{i1}, Q_{i2}, Q_{i3}\}$ for t=5 and so on. Moreover, the total error term in the production function is assumed to be uncorrelated with the lagged difference of the outcome variable starting from time t=3. This generates GMM-type instruments for the level equation as below:

$$[\Delta Q'_{it-1}(\mu_i^{Q} + \varepsilon_{it}^{Q})] = 0 \quad \text{for t>=3}$$

GMM-type instruments as explained above can be constructed for the other outcome variables and the variables in the vector *R* in equations (1) and (2). In order to obtain consistent GMM estimates, we first need to check the presence of second order autocorrelation in the first difference equation (this is equivalent to checking whether the error terms in the level equation are serially uncorrelated or not) and second we need to check if overidentifying restrictions are valid using a Sargan test, which asymptotically follows a chi-squared distribution. As a result, coefficient estimates from a hybrid production function are obtained by estimating equations (1) and (2) jointly using a two-step system GMM estimator with the Windmeijer (2005) correction for standard errors.

4.1. Other Instruments

The inclusion of exclusion restrictions in addition to GMM-type instruments constructed from the lags of endogenous variables improves efficiency and are needed since GMM-type instruments are not used for all lagged variables.[16] Those instruments affect the final outcome variable only through their effects on endogenous explanatory variables. Since ECLS-B data do not include any state/county-level variables that can be used as instruments, the original ECLS-B data are merged with state/county

[16] Exclusion restrictions are called external instruments in the system GMM framework. The decision to use GMM-type instruments for all or some of the variables depends on how autocorrelation and Sargan test results change with the inclusion of GMM-type instruments.

variables using the state and zip code information in the data set.[17] These are the county-level unemployment rate, poverty rate, service sector employment per capita, goods sector employment per capita, average state-level wage rate per hour, the TANF state expenditures per capita, county-level median household income per capita, the county-level male-female ratio for individuals over 18 years old, average state level child care prices,[18] the per capita county-level number of day care establishments, the per capita state-level number of regulated center-based child care places and family-based child care places, the state-level mean wage of preschool teachers and child care workers, state-level two-year public and four-year public and private university costs for tuition, the 95th percentile for the state-level precipitation measure and standard deviations for state-level rain and snow fall.

4.2. State/County-Level Variables

The state/county-level variables described below are assumed to affect the distribution of prices for the unobserved variables and generate exogenous changes in the consumption of unobserved inputs. Some of those variables include the county-level number of supermarkets and grocery stores, the number of fruit and vegetable markets, convenience stores, museums, parks, fitness centers, zoos, and full-service and limited-service restaurants. These variables are likely to impact outcomes of children by affecting their food consumption and physical activities such as exercise, walking, and going to a zoo or a museum. The county-level total number of hospitals, number of short-term general hospitals with child wellness, short-term general hospitals with nutrition programs, short-term and long-term children's psychiatric hospitals, short-term general hospitals with psychiatric services for children and adults and dentist offices are also included. These variables are likely to impact the health and cognitive progress of children by affecting medical care and preventive care use by families. The county-level establishments for office supplies and stationery stores are also included, which might affect the number of materials available to the child at home and/or in a non-parental child care setting.[19]

5. RESULTS

In this section, Fixed Effects (FE), Random Effects (RE) and two-step system GMM estimation results of the production function are compared. RE models do not control for unobservables while the FE models control only for permanent unobserved heterogeneity. Two-step system GMM models handle the endogeneity problem resulting from both time-invariant and time-varying unobservables. In Table

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[17] A complete list of summary statistics for the state/county-level variables is in the PhD thesis and available upon request.

[18] i.e., state-level average annual cost of infant care for center-based settings and state-level annual average cost of preschool care for center-based settings from reports published by NACCRRA, the National Association of Child Care Resource & Referral Agencies.

[19] The details about the construction of state/county variables along with their summary statistics can be found in the PhD thesis and available upon request.

3 and Table 4[20], for the RE and FE models, Model 1 does not include the quality variables and exogenous child and mother characteristics and exogenous state/county-level variables. Model 2 adds quality variables into the model and Model 3 includes both quality variables as well as exogenous child and mother characteristics and state/county-level variables. For GMM models, Model 2 adds quality variables into the model in addition to the variables in Model 1 and both models include exogenous variables. Two different specifications of hours of work and child care are defined. The first specification assumes that a mother can choose any continuous hours of work and hours of child care types i.e., center-based and home-based. The second specification assumes that a mother may face restrictions on the choices of hours of work – which may be more plausible assumption than continuous choices, and child care types. The most common discrete choices of hours of work in the labor supply literature are full-time work, part-time work and no work. Similarly, center-based (home-based) child care hours are defined as full-time center (home-based), part-time center (home-based) and no use of center-based (home-based) child care. Hence, this specification will show us whether there are any nonlinearities in the effects of hours of work and hours of childcare.

As shown by RE models in Table 3, adding quality variables increases the effects hours of work and hours of child care variables while inclusion of exogenous variables leads to small decreases in the magnitude of home quality variable. All the FE models have smaller effects for hours of work, hours of child care and quality variables. However, the sign of the out-of-home quality variable is negative with the FE model, which is not theoretically true. Thus, these results suggest that unobserved time-invariant variables that are correlated with the maternal employment and child care choices cause upward bias in the estimates if they are ignored. For instance, if the child's cognitive skill endowment is high (positively correlated with the child's cognitive achievement), the mother might be comfortable working more hours and, thus, use more child care. Moreover, if a mother's productivity both at home and work are positively correlated so that child's cognitive development will improve and she will be working more hours (and using more child care), then the estimated coefficients will be biased upward. The two-step system GMM estimates for the coefficients of hours of work, hours of center-based care and home-based care and quality variables are all greater than the RE and the FE models which implies that not controlling for time-varying unobservables lead to downward biased estimates. For example, if the child experiences a developmental delay worsening over time, a mother might be motivated to find high-quality child care that generates downward bias in the estimated child care and quality variables. Another example might be that she may lose her interest or skills in child rearing over time while intending to work more hours. In addition, if she develops maternal stress over time (e.g., due to working more hours), which worsens a child's cognitive achievement, she might increase the use of child care. All of this might lead to a downward bias in estimated coefficients. Inclusion of quality variables as shown in

[20] Coefficient estimates for the rest of the variables are not shown here in order to save the space but they are all available upon request.

the last column of Table 3 increases the impact of hours of work while reducing the effect of center-based care. A 10-hour weekly increase in the use of center-based care today leads to 0.30 SD (standard deviation) increase in child's cognitive achievement next period ($p < 0.01$). Moreover, a 1 SD increase in the home quality index increases the cognitive achievement of the child by 0.10 SD at 1% significance level. A 1 SD increase in out-of-home child care increases the cognitive achievement of the child by almost 0.35 SD ($p < 0.01$).

As shown by RE Models 1-3 in Table 4, maternal work and center-based care variables are significant and their effects are slightly larger when quality and exogenous variables are included. Home quality and out-of-home child care quality variables are also significant. FE Models 1-3 estimate smaller effects for all variables and a negative effect for home-based child care. Magnitude of the coefficient estimates with GMM models are all greater than that of RE Model 3 and FE Model 3 which implies that ignoring time-varying unobservables leads to downward bias in estimates. Neither full-time work nor part-time work is significant while both full- and part-time center-based child care have significant effects on cognitive achievement of the child. Inclusion of quality variables in the GMM model increases the effect of full-time center-based care while it reduces the impact of part-time center-based care. Consistent with the findings from Table 3, center-based care has significant positive effects on cognitive achievement. Full-time center-based child care compared to no center-based care increases the cognitive achievement of the child by 1.73 SD ($p < 0.01$). Additionally, part-time center-based child care when compared to no child care improves cognitive achievement of the child by 0.74 SD ($p < 0.01$). On the other hand, home-based child care variables are not significant. Moreover, a 1 SD increase in the home quality index increases cognitive achievement of the child by almost 0.12 SD at 1% significance level and a 1 SD increase in out-of-home child care increases cognitive achievement of the child by 0.37 SD ($p < 0.01$).

Consistency of the system GMM approach requires no second order autocorrelation in the first difference error terms as well as valid overidentifying restrictions. As shown in Table 3 and Table 4, p-values for autocorrelation test results imply that there is no second order autocorrelation in the first difference error terms and we cannot reject the null hypothesis, which states that the overidentifying restrictions are valid by looking at the p-values for the Sargan tests.

Table 3. Marginal Effects from the Estimation of Production Function for Cognitive Achievement (Specification 1)

	RE Model			FE Model			GMM Model	
	(1)	(2)	(3)	(1)	(2)	(3)	(1) [1]	(2) [2]
Hours of work[a]	0.006	0.009**	0.008**	0.002	0.003	0.004	0.047	0.071
	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.007)	(0.008)
Center-based	0.030**	0.034**	0.034**	0.028**	0.027**	0.023**	0.282***	0.303***
child care hours[a]	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.009)	(0.009)
Home-based	0.002	0.005	0.007	-0.008	-0.010*	-0.010*	0.102	0.075
child care hours[a]	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)	(0.001)	(0.010)	(0.007)
Home quality		0.082**	0.074**		0.056**	0.057**		0.104***
index		(0.007)	(0.007)		(0.009)	(0.009)		(0.022)
In-home child care		0.024	0.017		0.009	0.006		0.040
quality index		(0.025)	(0.025)		(0.026)	(0.026)		(0.041)
Out-of-home child care		0.009	0.011		-0.001	-0.003		0.346***
quality index		(0.010)	(0.010)		(0.010)	(0.010)		(0.128)
Obese	-0.065***	-0.064***	-0.062***	-0.084***	-0.083***	-0.083***	-0.055	-0.131***
	(0.019)	(0.019)	(0.019)	(0.022)	(0.022)	(0.022)	(0.169)	(0.045)
Exogenous Variables	No	No	Yes	No	No	Yes	Yes	Yes
AR(1): -6.776 (p-value: 0.000)								
AR(2): -1.503 (p-value: 0.133)								
Sargan: $x^2(56)$=69.147 (p-value: 0.112)								

Notes: Sample size, 20850, is rounded to the nearest 50 as required by NCES. Standard errors in parentheses. *p<0.10 **p<0.05 ***p<0.01
[a] Coefficients are reported for 10 hours. Numbers in square brackets [.] show GMM model number.

Table 4. Marginal Effects from the Estimation of Production Function for Cognitive Achievement (Specification 2)

	RE Model			FE Model			GMM Model	
	(1)	(2)	(3)	(1)	(2)	(3)	(1) [25]	(2) [26]
Full-time work	0.032*	0.047***	0.043**	0.014	0.021	0.020	-0.373	0.150
	(0.017)	(0.017)	(0.017)	(0.022)	(0.022)	(0.022)	(0.389)	(0.394)
Part-time work	0.058***	0.058***	0.050***	0.029	0.031	0.027	-0.695*	0.112
	(0.017)	(0.017)	(0.017)	(0.022)	(0.022)	(0.022)	(0.355)	(0.317)
Full-time center-based care	0.124***	0.154***	0.155***	0.110***	0.115***	0.103***	1.584***	1.727***
	(0.023)	(0.025)	(0.024)	(0.027)	(0.029)	(0.029)	(0.553)	(0.534)
Part-time center-based care	0.115***	0.134***	0.128***	0.127***	0.130***	0.112***	1.007***	0.742***
	(0.017)	(0.020)	(0.020)	(0.019)	(0.022)	(0.022)	(0.276)	(0.227)
Full-time home-based care	0.001	0.018	0.027	-0.054**	-0.060**	-0.057**	0.801*	0.696
	(0.021)	(0.022)	(0.022)	(0.025)	(0.026)	(0.026)	(0.475)	(0.442)
Part-time home-based care	0.004	0.012	0.017	-0.001	-0.006	-0.008	0.389	0.257
	(0.016)	(0.017)	(0.016)	(0.019)	(0.020)	(0.019)	(0.335)	(0.356)
Home quality index		0.080***	0.072***		0.054***	0.056***		0.115***
		(0.007)	(0.007)		(0.009)	(0.009)		(0.024)
In-home child care quality index		0.024	0.017		0.009	0.005		0.044
		(0.025)	(0.025)		(0.026)	(0.026)		(0.042)
Out-of-home child care quality index		0.014	0.016*		0.003	0.001		0.372***
		(0.010)	(0.010)		(0.010)	(0.010)		(0.127)
Exogenous Variables	No	No	Yes	No	No	Yes	Yes	Yes
AR(1): -8.491 (p-value: 0.000)								
AR(2): -0.999 (p-value: 0.318)								
Sargan: $x^2(93)$=108.942 (p-value: 0.124)								

Notes: Sample size, 20850, is rounded to the nearest 50 as required by NCES. Standard errors in parentheses. *p<0.10 **p<0.05 *** p<0.01. Numbers in square brackets [.] show GMM model number.

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6. CONCLUSION

This research analyzes the effects of maternal employment and non-parental child care on the cognitive development of children in early childhood. The hybrid production function in a dynamic framework is estimated controlling for the endogeneity of observed inputs using a two-step system GMM estimator. The ECLS-B, a nationally representative data set, is used to estimate the model. This data set provides information on child nutrition, parenting style, and home and child care environments. Using this information, the non-parental child care and home quality indices are estimated from the first principal components derived from a factor analysis. All models are estimated with those quality indices because child care is a service with heterogeneous quality and the quality of a child's home environment differs by parenting style and nutritional choices of the mother.

A comparison of two different specifications reveals that the effects of quality variables are robust across specifications. The effect of home quality is around 0.10 SD. The effects of out-of-home child care quality vary between 0.35 and 0.37 SD. This indicates that high-quality child care services received outside of a child's home have much more impact than the quality of home environment on the cognitive development of children. At the same time, quality of child care received at home does not have any significant effect on the cognitive development. This finding might be explained by the fact that child care centers provide age-appropriate curriculum and children have more opportunities to interact with their peers in such an environment. In addition, more hours of center-based care significantly improves cognitive achievement and this holds true when full- or part-time center-based care is used (compared to no center-based care), as in specification 2. On the contrary, home based child care does not have significant impact on the cognitive development. This results is consistent with the literature in which spending more time in a formal child care setting has been shown to improve cognitive skill development. We observe that maternal work do not have statistically significant effect on the cognitive development when the endogeneity is controlled for using FE and GMM models. That is, the significant effect seen in RE models are resulted from the unobservables (e.g., child's unobserved ability level) that are correlated with both the child's cognitive skill and the mother's work decision. Moreover, across all specifications, omission of quality variables alters the magnitude and significance of maternal work and child care variables, which have theoretically expected signs when unobserved heterogeneity is controlled using the GMM estimator. For instance, as can be seen in specification 2 sign of maternal work changes and impact of full time center based care increases when quality variables are added.

Early childhood is an important period in which a child's both cognitive and non-cognitive skills such as emotions, personality, social interaction, attention and concentration are formed. While this study considers the effects of child care on the cognitive development of children, non-parental child care has considerable impact on the development of non-cognitive traits. The reason is that especially in formal child care settings interaction with child caregiver and other children help improve the child's non-cognitive skills in an effective way. Hence, the effect of child care on non-cognitive skill development can be investigated with this data set in a future study. In summary, not only the amount of time spent in a child care setting but also the quality of the time spent in child care and at home significantly improve the cognitive development. Since quality of child care is not homogenous and its price vary significantly between different child care places, public policies should be developed in order to make child care affordable for low income families. Contrary to the child care variables, effect of maternal work is found to be insignificant on the cognitive skills when the endogeneity is taken into account. Thus, another future research may also consider to estimate child outcome and mother's choices jointly in order to improve the efficiency of the estimates when controlling for the endogeneity of the variables of interest.

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