Effects of Maternal Employment and Child Care on the Health of Young Children

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A dissertation submitted to the faculty of the University of North Carolina at Chapel Hill in partial fulfillment of the requirements for the degree of Doctor of Philosophy in the Department of Economics.

Chapel Hill
2009

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Abstract

MAI NOGUCHI HUBBARD: Effects of Maternal Employment and Child Care on the Health of Young Children
(Under the direction of Donna Gilleskie)

Over the past several decades, the United States has witnessed a significant increase in the prevalence of overweight and obese children. Given that the immediate and long-term implications of obesity on a child's physical and emotional well-being can be severe, biomedical researchers, social scientists, and the general public have made an aggressive push towards finding an explanation for what some have now deemed a national health epidemic. Despite a large body of empirical research on the impact of environmental, behavioral, and societal factors on the obesity increase in the past thirty years, surprisingly little attention has been devoted to examining the impact of one notable change occurring during the same time period: an increase in women's labor force participation, and consequently an increase in child care usage. This three chapter dissertation examines the effects of maternal employment and usage of non-parental after- and/or before-school supervision on elementary school-age children's body mass statuses.

In the first chapter, I examine the impact of mothers' employment and non-parental after- and/or before-school care choices on three alternative body mass outcomes: risk of overweight, risk of obesity, and BMI-percentile-for-age-and-sex. In the second chapter, I exploit the availability of information on the type of non-parental supervision received (i.e., informal care with a relative, such as grandparents or siblings; informal child care with a non-relative, such as a babysitter; and formal child care) to analyze differences in the effect of child care on body mass status by type of setting. In the final chapter, I consider the density of BMI-for-age-and-sex as the specification of body mass status. I apply a flexible estimation technique, the conditional density estimation method, that discretely approximates a density function of the body mass status outcome. This approach allows covariates, such as employment and child care, to have

different effects at varying levels of body mass status.

To my husband and best friend Justin, for always standing by me.

Acknowledgments

This dissertation could not have been completed without the help and support of many individuals. First and foremost, I am forever indebted to my advisor, Donna Gilleskie, for her unwavering support and continued guidance. In addition, I would like to thank the other members of my committee, Helen Tauchen, David Guilkey, John Akin, and Sally Stearns, for their invaluable suggestions and comments. I must also thank Peter Lance, who never discouraged me from asking questions and helping me to transition from student to researcher.

I am extremely grateful to all of my family members. Mom and Dad, you have given me the courage to continue graduate school and I cannot adequately express my love for you. You have sacrificed so much for me and I don't think I can ever thank you enough for all that you have done. Thank you, Dr. and Mrs. Hubbard for all your years of support and never doubting in me. Dylan, Seth, and Laurie, I could not have asked for better siblings and I am so thankful to have all of you.

Finally, I wish to thank my husband Justin from the bottom of my heart. Your confidence in me and your words of encouragement have meant the world to me. I have come this far because of you.

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Chapter 1

The Effect of Mothers' Employment and Child Care Decisions on the Body Mass Status of Young Children

1.1 Introduction

Over the past several decades, the United States has witnessed a significant increase in the prevalence of overweight and obese children.[1] An analysis of the National Health and Nutrition Examination Survey (NHANES) data reveals that obesity rates between 1976 and 2004 increased from 6 to 19 percent for children ages 6 to 11 and from 5 to 17 percent for young adults ages 12 to 17 (Centers for Disease Control and Prevention, 2007).[2] Given that the immediate and long-term implications of obesity on a child's physical and emotional well-being can be severe, biomedical researchers, social scientists, and the general public have made an aggressive push toward finding an explanation for what some have now deemed a national health epidemic.

In this paper, I add to the current research on childhood obesity by examining the effects of two notable changes that have coincided with the rise in childhood obesity prevalence: an

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[1]It should be noted that the rise in the prevalence of overweight and obese individuals is not unique to the United States. Globally, over 1 billion adults are overweight (WHO, 2008).

[2]Typically, obesity and overweight statuses are determined using a measure called Body Mass Index (BMI) which is a ratio of weight in kilograms to height in meters squared. Individuals with a BMI between 25 and 30 are considered overweight; between 30 and 35 obese; and greater than 35 morbidly obese. Body mass statuses of children (ages 2-20) are determined using BMI-for-age-and-sex percentiles. A more detailed discussion of this topic can be found in Section 1.5.1.

increase in maternal employment and in non-parental child care usage (most likely due to the growth in women's labor force participation).[3] Without further empirical investigation, it is difficult to predict whether these decisions will negatively or positively influence children's body masses. For instance, children of working mothers may eat fewer home-cooked meals and more high-calorie fast foods or pre-cooked meals. In addition, they may spend more time unsupervised and engaging in sedentary activities such as playing computer and video games (Anderson et al., 2003). On the other hand, working mothers may be able to provide healthier meals and enroll their children in physically active after-school programs with their income (Fertig et al., 2006). Furthermore, if mothers who work outside of the home are more likely to have higher self-esteem then the quality of time spent with their children may improve.

Similarly, the impact of participation in non-parental child care (referred from this point on as simply "child care") on children's body mass health is not clearly understood. Some researchers posit that child care workers may be less attentive to the individual health needs of each child and as a result, consumption of processed and non-perishable foods (i.e., canned and frozen fruits and vegetables instead of raw), that often contain large amounts of sugar and preservatives, may be more frequent. On the contrary, if centers adhere to regimented activity and eating schedules children in child care settings may be more likely to engage in rigorous activities and eat nutritious meals and snacks.

The current literature with regard to women's labor force participation and usage of child care has focused primarily on their impact on children's cognitive and behavioral outcomes (and the findings in these papers are quite mixed). Furthermore, in spite of the strong link between mothers' employment participation and children's usage of child care, the available literature examines the effect of the two factors separately. This potential shortcoming does not consider that mothers often make decisions about employment *jointly* with their child care decision.

Using the Early Childhood Longitudinal Survey-Kindergarten Class of 1998 (ECLS-K), a nationally representative survey of children who attended kindergarten in 1998, I evaluate the

[3] I look specifically at maternal employment (and not paternal) because the increase in obesity prevalence has coincided with women's entry into the labor force (Anderson et al., 2003) and also because past studies have been unable to find a significant relationship between paternal employment and a child's health outcome.

impact of mothers' employment and child care decisions on the body mass statuses of *elementary school-age* children. This survey provides a unique opportunity to examine a group of children who spend a majority of their day in school, but may also use child care in the form of before- or after-school care.

In estimation, I consider an endogeneity issue stemming from two potential sources: first, there may be unobservable characteristics of the mother or child that influence the decision to work or to use child care that also affect health and second, there may be simultaneity between a mother's employment and child care decisions, and the body mass status of her child. The former issue is resolved by jointly estimating an equation representing the joint demand for employment and child care with the health production equation allowing the error components to be correlated both contemporaneously and over time. The latter issue of reverse causality is addressed using a dynamic framework.

To this end, I estimate the causal impact of maternal employment and child care on children's body mass statuses using a flexible full-information maximum likelihood estimation technique: the discrete factor random effects estimation method. Simulations conducted in this paper indicate that there is a significant reduction in the risk of obesity when mothers work full-time and do not use child care compared to if they were to not work and not use child care. On the other hand, for full-time working mothers I find that using child care increases the risk that a child is obese and overweight.

1.2 Background

1.2.1 Consequences of Childhood Weight Problems

Children who are obese frequently suffer from physical and emotional ailments including sleep apnea, orthopedic conditions, asthma (Paxson et al., 2006), and depression (Daniels, 2006). They are also at higher risk of developing chronic illnesses, such as heart disease and Type II diabetes, that can require long-term disease management. One major concern has been that illnesses that were once only seen in adults (e.g., Type II diabetes, hypertension, etc.) are now being diagnosed in young children.

In addition, problems related to childhood obesity can extend beyond the medical and physical by imposing significant economic burden to individuals, their families, and to society. Paxson et al. (2006), for example, cite increases in childhood obesity-related hospital expenditures from 25 to 127 million dollars between the late 1980s and late 1990s. Whitaker et al. (1997) also find that children who are overweight or obese are more likely to face weight problems as adults. In addition, evidence suggests that women who are overweight as adolescents are more likely to have "less education, lower earning power, a higher likelihood of poverty, and a lower likelihood of marriage" (Daniels, 2006). Increasing awareness of obesity and its health and economic consequences has led to a growing literature on the causes and effects of obesity within the economics and biomedical professions.

1.2.2 Possible Causes of Childhood Weight Problems

Thus far, it is clear to researchers that the physiological process of weight gain is a direct consequence of consuming more calories than are expended over time. Finding an explanation for why behaviors in diet and activity have changed over the past several decades is, however, a much more complex issue because of the interplay between societal, environmental, genetic, and individual factors that can potentially affect energy balance. Within the economics field, the majority of studies on this health topic (to my knowledge) focus on finding explanations for adult, rather than childhood, obesity. Although both occur as a result of an excess in caloric intake to expenditure, children are potentially more susceptible to changes in the environment (e.g., increases in the availability of sugary drinks and fast food restaurants) that encourage negative health behaviors because they often have very little control over their own health input choices.

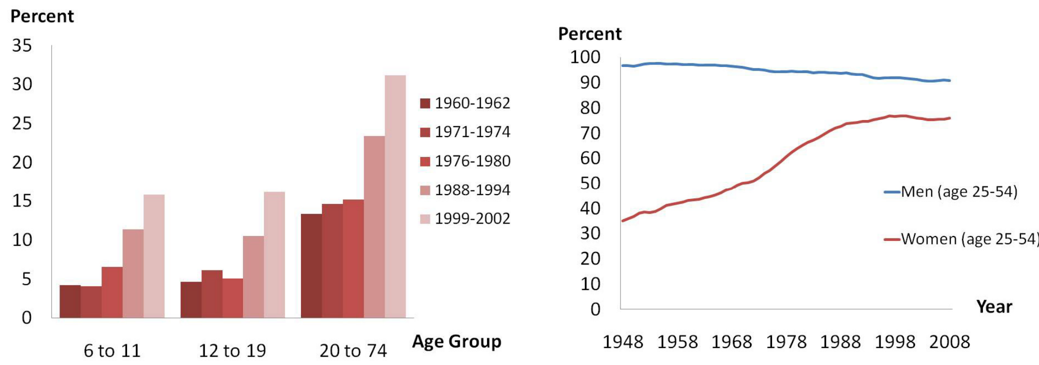
An oft-cited explanation for rising obesity are advancements in technology, that have reshaped the American lifestyle (Philipson and Posner, 2003; Lakdawalla and Philipson, 2002; Cutler and Shapiro, 2003). Philipson and Posner (2003) and Lakdawalla and Philipson (2002) theorize that shifts in the workforce environment from an agriculturally intensive one to that of a more sedentary nature have led to an increase in the cost of expending energy and a decline in the real price of food. The authors explain that agrarian societies pay individuals to be physically active, whereas residents of industrialized societies must bear the burden of exercise costs in the form of foregone leisure. An empirical analysis of this hypothesis by Lakdawalla and Philipson (2002) finds that declines in job strenuousness increase individuals' weights. Cutler and Shapiro (2003), on the other hand, argue that technological changes have cut down on the cost and production time of food.

A large body of empirical studies within the biomedical literature finds deleterious effects of increases in consumption of junk and restaurant foods, high fructose beverages, and pre-cooked (or pre-packaged) meals that are often laden with fats on childhood (and adult) obesity. MacInnis and Rauser (2005) for example, examine the effect of processed foods, which are characteristically energy dense (i.e., high number of calories per gram of food), on children's obesity risk using a fixed effects estimation approach. They find that consumption of foods that are high in energy density can increase the risk of being overweight by around 14 percentage points, even after controlling for total caloric intake and expenditure.

1.2.3 Effect of Employment and Child Care on Children's Body Mass Statuses

One growing area of research examines changes within the American family structure, which has undergone significant modifications since the 1970s, to explain rising childhood obesity. In particular, the percentage of mothers participating in the labor force has increased from approximately 38 to 68 between 1970 and 2000 (Story et al., 2006). Consequently, child care usage has also grown; the U.S. Census Bureau estimates that 63% of children between the ages of 6 and 14 participate in some type of before- and after-school child care (Story et al., 2006). Figure 1 presents rates of obesity (National Health and Nutrition Examination Surveys) from 1960 and 2002 and labor force participation rates of men and women between the ages of 25 and 55 (U.S. Census Bureau) from 1948 and 2008. Labor force participation rates of women increased dramatically in the mid-1970s (see b), which corresponds to the time period in which obesity rates of children also increased (see a).

In light of increases in women's labor market participation, several papers have recently investigated its effect on children's risk of being overweight. Anderson et al. (2003) and



(a) Obesity Trends: 1960-2002 (b) Labor Force Participation: 1948-2008

Figure 1.1: Obesity and Labor Force Participation Trends

Courtemanche (2007) estimate the effects of maternal employment on childhood obesity using differencing estimation methods (i.e., first and long differences) to control for potential unobserved heterogeneity. Both papers find a positive and statistically significant correlation between employment and obesity. Furthermore, Anderson et al. show that this effect is more pronounced for children of higher economic status. These papers, however, are unable to account for time-varying unobservable variables that may be influencing mothers' employment and child care decisions and children's obesity risk. For instance, unobserved changes over time in the child's physical or emotional well-being may influence a mother's decision to work as well as her child's body mass status. Similarly, Phipps et al. (2005) and Classen et al. (2005) find positive effects of maternal employment on children's risk of obesity, but do not control for potential unobserved variables that may bias these estimation results. Lastly, Fertig et al. (2006) and Cawley and Liu (2007) examine the mechanisms through which employment influences children's risk of being overweight. Cawley and Liu (2007) suggest that maternal employment may have contributed to rising obesity by decreasing her time spent cooking and playing with the children and increasing the consumption of pre-cooked meals.

Research on the effects of child care on childhood obesity remains scarce. In one study Frisvold (2006) studies the effect of Head Start programs, which provide a wide array of services to poor and disabled children including nutritional services, on children's risk of being overweight. He finds that participation in the program significantly reduces the probability of becoming overweight or obese in later childhood for black participants. His paper, however, is limited in scope since the analysis is specific to low-income family children that are enrolled in the program.

1.2.4 Overview

This paper provides additional evidence of the impact of maternal employment on child body mass status and contributes to the current research in several ways. First, using a dynamic framework I model the maternal employment and child care choices as joint decisions. I simultaneously estimate the employment and child care decisions with the child's health outcome to allow for correlations in unobserved variables across equations. Second, I not only control for individual permanent heterogeneity, but also model the time-varying unobservables that may be correlated with the joint employment and child care decision, and child health over time. Third, I address the void in the current literature on the effects of child care on body mass dynamics.

1.3 Theoretical Motivation

The theoretical model in this section motivates the empirical specification of the employment and child care demand and body mass production equations described in Section 1.4. In addition to providing a theoretical foundation for the empirical model, this section explains why and how the child's body mass production equation is transformed from a function of child inputs exclusively to one that depends on mother's hours of employment and on the child's hours of non-parental child care. Secondly, it provides a theoretical explanation of the sources of identification relevant for estimation of the model.

In general, longitudinal US data that include information on food consumption, time use, and physical outcome measures are difficult, if not currently impossible, to obtain. The data set I use, which includes child's body mass measures over time, does not report a child's time use or food consumption, but does distinguish between two types of mother's time: time spent working and leisure, which includes the mother's time spent in activities devoted to herself and time spent caring for her child (such as driving the child to activities, preparing healthy meals, and engaging in healthy activities). Therefore, due to data limitations, I cannot estimate the demand for a child's food and activity levels, estimate the effects of these physiological input behaviors, nor estimate the effects of a mother's direct participation in these activities on child health. In addition, I am unable to quantify the tradeoff between the mother's individual time and time spent directly with her child, nor the tradeoff between her own consumption (for food, apparel, books, etc.) and that of her child as it relates to a child's body mass status. The theoretical discussion that follows anticipates these data challenges.

1.3.1 Key Features of the Model

The theoretical framework is consistent with Grossman's (1972) seminal work on the theory of individual health care demand where better health, rather than the direct consumption of health inputs, provides happiness. Individuals consume health inputs in order to produce health: a capital good. In my model, the mother derives utility in each period t from the health status of her child, her own time spent in leisure, and consumption. Her child's health (i.e., body mass status) is determined by lifestyle behaviors (i.e., caloric intake and caloric expenditure) that may be influenced by her choice of employment and child care hours. Unlike previous studies where the effects of maternal employment were examined using a static framework, the dynamic model applied here allows the mother's decisions at time t to influence her contemporaneous utility as well as her future utility (via her child's body mass status). The sequential decision making behavior of the mother is characterized as follows:

1. At the beginning of each period the mother observes the health of her child; her wage; prices of child care, food, activities, and consumption goods (e.g., apparel, books, etc.); and her preferences for work and child care.

2. Given this information, she chooses the number of hours to work and the number of hours of child care to use (first stage of optimization problem). These decisions determine her disposable time and money.

3. Upon deciding hours of employment and child care, she observes her per-period preferences

for allocation of remaining time and money during the period. The mother then allocates her remaining pecuniary and time resources to her and her child's consumption and time spent for herself and her child, respectively (second stage of optimization problem).

4. Choices made during the period affect the child's health transition, with the health outcome being observed at the beginning of the next period.

1.3.2 Optimization Problem

Conventionally accepted measures of body mass status (B_t) depend, biologically, on calories consumed (I_t) and expended (E_t), and the physiological relationship between these factors is rather straightforward.[4] The CDC (2008) describes being overweight and obese (measures of body mass status described in greater detail in Section 1.5.1) as a "consequence of energy imbalance over time"where energy imbalance is a "condition where calories consumed is [greater than] calories expended". Therefore current period body mass status and the difference between caloric intake and expenditure characterize an individual's body mass status in the following period.[5] Energy balance, however, is influenced by a host of environmental, societal, and genetic factors whose relationship with body mass status is much more difficult to comprehend. A child's time spent with the mother versus the child's time spent in child care, for instance, may potentially influence a child's quality and quantity of foods and participation in activities.

The mother allocates her time and money to maximize lifetime utility subject to several per-period constraints. At the beginning of each period, the mother receives a draw from a distribution of hourly wages and one of hourly child care prices, and observes her preferences for employment and child care (ν_t^1). Her first stage alternatives include combinations of employment hours (H_t) and child care hours (C_t). In the second stage of each period t, shocks to preferences for consumption and time allocation are revealed (ν_t^2). Conditional on employment and child care hours, she allocates her disposable income to three consumption goods that

[4]Body mass status (B_t) can be characterized as a continuum (e.g., BMI or Body Mass Index) or categorically (e.g., ideal body weight, overweight, obese).

[5]It should be noted that for children, calories expended also includes energy required for normal growth and development.

include her consumption of composite commodities (G_t^M) and purchases related to the child's caloric intake (G_t^I) and expenditure (G_t^E). In addition, she allocates her disposable time to three forms of leisure that include the mother's own leisure (L_t^M) and her time related to her child's consumption of food (L_t^I) and activities (L_t^E). The mother derives utility (or disutility) from her own consumption (G_t^M) and leisure (L_t^M), child care (C_t), and her child's body mass status entering the period (B_t). Her utility also depends on a vector of exogenous preference shifters (X_t) and the preference error vector denoted by $\nu_t = [\nu_t^1, \nu_t^2]$. Specifically, her lifetime utility is:

$$\mathrm{E}\left[\sum_{t=1}^{T} \beta^t U_t\left(G_t^M, L_t^M, C_t, B_t; X_t, \nu_t\right)\right] \tag{1.1}$$

where $U_t(\cdot)$ is the utility function, β is the discount factor, and E is the expectations operator.[6]

The child's body mass outcome in period $t+1$ (B_{t+1}) depends on body mass status at time t (B_t), caloric intake (I_t) and expenditure (E_t), and a vector of observable characteristics of the child (also included in the vector X_t), such as age and sex, that can influence the conversion of calories into body mass. Specifically, this production function is

$$B_{t+1} = B(B_t, I_t, E_t, X_t). \tag{1.2}$$

Caloric intake (I_t) and expenditure (E_t) are functions of child caloric intake- and expenditure-related purchases (G_t^I and G_t^E, respectively) and caloric intake- and expenditure-related time (L_t^I and L_t^E, respectively) and are written

$$I_t = I(G_t^I, L_t^I) \tag{1.3.a}$$

$$E_t = E(G_t^E, L_t^E). \tag{1.3.b}$$

Drawing from a distribution of wages and child care prices the mother obtains an hourly wage (w_t) were she to work and child care price (p_t^c) were she to use child care. The distributions of these prices depend on county- and state-level characteristics denoted by $Z_t = [W_t, P_t^c]$.

[6] I drop the individual subscript i in this section for notational simplicity.

The mother's first stage decision regarding employment and child care hours define disposable income (Y_t^D) and disposable time (L_t^D). That is,

$$Y_t^D = w_t H_t + Y_t - p_t^c C_t, \tag{1.4}$$

where Y_t denotes non-earned income and is henceforth included in the vector X_t, and

$$L_t^D = \Omega - H_t, \tag{1.5}$$

where Ω denotes the total hours in one week.

In the second stage the mother allocates her disposable income (Y_t^D) between purchases related to the child's caloric intake (G_t^I) and expenditure (G_t^E) and her own consumption good (G_t^M), where

$$G_t^M = Y_t^D - (p_t^I G_t^I + p_t^E G_t^E). \tag{1.6}$$

Prices of goods related to the child's caloric intake (p_t^I) and expenditure (p_t^E) are drawn from distributions of prices that depend on county- and state-level characteristics that are denoted by a vector $P_t = [P_t^I, P_t^E]$. In addition, she also allocates her disposable time between that devoted to the child's consumption of food (L_t^I) and activities (L_t^E) and time spent in other non-market activities (L_t^M), such that

$$L_t^M = L_t^D - (L_t^I + L_t^E). \tag{1.7}$$

1.3.3 Solution to the Model

The demand equation for the joint maternal employment and child care decision is a function of health status in period t (B_t), observable characteristics of the mother and child (X_t), county- and state-level food and activity prices and availability (P_t), and exogenous time-varying county- and state-level variables that are likely to influence wage offers and child care prices (Z_t). Thus, the joint demand for employment and child care is

$$
\begin{aligned}
H_t^* &= H(B_t, X_t, P_t, Z_t) \\
C_t^* &= C(B_t, X_t, P_t, Z_t). \qquad (1.8)
\end{aligned}
$$

The value of lifetime utility in the second stage of the period does not depend on characteristics of the distribution of wages and child care prices (Z_t), conditional on the first stage alternatives $H_t = h$ and $C_t = c$, and the realized wage and child care values that define Y_t^D. Therefore, the optimal demand equation for the mother's consumption goods (G_t^{M*}), and analogously her leisure (L_t^{M*}), conditional on the joint employment ($H_t = h$) and child care decision ($C_t = c$), is a function of weight status (B_t), observable exogenous characteristics (X_t), and food and activity prices drawn from a distribution of community characteristics ($P_t = [P_t^I, P_t^E]$). Similarly, the same arguments explain optimal purchases for and time devoted to the child's intake and expenditure ($G_t^{I*}, G_t^{E*}, L_t^{I*}, L_t^{E*}$). Specifically,

$$G_t^{j*} = G^j(B_t, X_t, P_t | H_t = h, C_t = c) \quad \forall j = M, I, E \qquad (1.9.a)$$

$$L_t^{j*} = L^j(B_t, X_t, P_t | H_t = h, C_t = c) \quad \forall j = M, I, E. \qquad (1.9.b)$$

Substituting equations (1.3.a) and (1.3.b) into equation (1.2), the body mass equation can be rewritten as

$$B_{t+1} = B(B_t, G_t^I, L_t^I, G_t^E, L_t^E, X_t). \qquad (1.2')$$

Substitution of the demand equations (equations 1.9.a and 1.9.b) into ($2'$) thereby yields

$$B_{t+1} = B(B_t, H_t, C_t, X_t, P_t). \qquad (1.2'')$$

Subsequently, equations $1.2''$ and 1.8 will provide the basis for the empirical specifications described in the following empirical section.

1.4 Empirical Model

1.4.1 Empirical Specification

I begin by specifying an equation for the joint demand for maternal employment and child care, and an equation for child health production derived from the theoretical model, which implies that the maternal employment and child care decisions are made simultaneously.[7] Therefore, in the empirical model I collapse the employment and child care alternatives into the following six mutually exclusive combinations:

$$d = \begin{cases} 0 & \text{if Not working and not using child care} \\ 1 & \text{if Not working and using child care} \\ 2 & \text{if Working part-time and not using child care} \\ 3 & \text{if Working part-time and using child care} \\ 4 & \text{if Working full-time and not using child care} \\ 5 & \text{if Working full-time and using child care} \end{cases} \tag{1.10}$$

where the joint decision variable representing hours of work ($H_t = h$) and hours of child care ($C_t = c$) per week is denoted $D_t = d$. I define an individual to be not working if $0 \leq h \leq 8$, working part-time if $8 < h \leq 35$, and working full-time if $35 < h$. I also define an individual to not be using child care if $0 \leq c < 5$ and using child care if $5 \leq c$. The decision to choose maternal employment and child care alternative d is a function of the child's body mass status entering the period (B_t), exogenous variables (X_t and P_t), and exclusion restrictions (Z_t).[8] The mother realizes her child's body weight status at the beginning of the next period. Thus, the child's body mass status at time $t + 1$ is a function of body mass status entering the period (B_t), maternal employment (H_t) and child care (C_t) choices, exogenous variables (X_t), and a vector of community-level variables (P_t). It should be noted once again that conditional on H_t and C_t, Z_t does not independently influence the child's body mass status.

[7] The individual subscripts, i, are dropped once again in this section for notational simplicity.

[8] Further detail on the exogenous variables (X_t and P_t) are provided in Section 1.5.2, and detail on the exclusion restrictions (Z_t) are provided later on in this section.

1.4.2 Estimation Strategy

If there are unobservable (to the researcher) mother or child characteristics that influence a child's health outcome that are also correlated with the maternal employment and child care decision, estimation of the body mass equation using common estimation techniques (e.g., Ordinary Least Squares, Logit, Probit, etc.) will result in biased estimates. Children's predisposition to poor health (a characteristic unobserved by the econometrician) for instance, may make mothers less likely to work, but more likely for the child to have poor health, resulting in an underestimation of the effect of employment on body mass status. Alternatively, the effect of child care on body mass may be overestimated if mothers with depression (another unobserved factor in the data) are more likely to receive help from family members in the form of informal child care and also more likely to have a child that is of unhealthy weight status. I address the potential endogeneity problem with two alternative estimation techniques: fixed effects, which controls for time-permanent heterogeneity; and a flexible random effects discrete factor estimation approach that models and estimates both the permanent and time-varying heterogeneity that may affect employment and child care demand as well as child health.

Fixed Effects

The fixed effects estimation approach requires repeated observations on an individual so that time-invariant unobserved heterogeneity can be eliminated. Despite its computational ease, several limitations exist. First, differencing cannot eliminate the correlation if factors such as the mother or child's attitudes change over time (i.e., factors which may be correlated with employment and child care demand, and child health). In fact, the effect of employment and child care on body mass will continue to be confounded by the effect of time-varying unobservables. Second, measurement error in the explanatory variables can exacerbate attenuation bias with this approach. Third, the method can only estimate marginal effects of those variables that vary over time (because variables that are time-invariant will be differenced out) and this may eliminate variables of interest to the researcher. In the same vein, since the fixed effects estimation approach identifies the effects of explanatory variables through changes in their values over time, there may be instances in which there is very little variation from which the effect is identified (resulting in inefficient estimates) (Angeles et al., 2008). Lastly, because the method requires the differencing of observations across time there can be a large loss in the degrees of freedom. In this paper for instance, with 18,990 individual-time observations, estimation via fixed effects will result in a loss of 6,330 degrees of freedom. An in-depth explanation of the fixed effects estimation technique is provided in Appendix A.1.

Discrete Factor Random Effects

My preferred estimation approach is the joint estimation of the maternal employment and child care demand equation with the health production equation using a flexible random effects estimation technique. In general, researchers that employ maximum likelihood estimation methods impose distributional assumptions, such as joint normality, about the error terms. The resulting estimates therefore hinge on the correctness of the specified distributional assumption. The discrete factor approximation method on the other hand, relaxes the distributional assumptions by allowing the unobserved heterogeneity components, both time-invariant and time-varying, to be approximated as a discrete step-wise function (see Heckman and Singer, 1984; Mroz and Guilkey, 1992; and Mroz, 1999). In practice, Mroz and Guilkey find that when the true distribution of the error terms is joint normal, discrete factor estimators are comparable to maximum likelihood estimators. In addition, when the true distribution is non-normal, discrete factor estimators perform better than maximum likelihood estimators in which joint normality is assumed. A detailed explanation of the discrete factor approximation method is available in Appendix A.2.

In estimation, I capture two sources of unobserved heterogeneity. First, I include a time-invariant permanent unobserved heterogeneity component that may influence a mother's joint employment and child care decision and child's health. Examples of such heterogeneity factors may include mother's ability or child's inherent health. The second source of heterogeneity is a time-varying component, such as a child's emotional or physical well-being that may change over time, but is unobserved (by the econometrician). I decompose the error terms for the employment and child care (ϵ_{1t}^d) and body mass status (ϵ_{2t}) equations into three components

$$\begin{aligned} \epsilon_{1t}^d &= \mu_1^d + \nu_{1t}^d + e_{1t}^d \quad d = 0, ..., 5 \\ \epsilon_{2t} &= \mu_2 + \nu_{2t} + e_{2t}, \end{aligned} \tag{1.11}$$

where μ_1^d and μ_2 capture the time-invariant permanent unobserved heterogeneity, ν_{1t}^d and ν_{2t} capture the time-varying unobserved heterogeneity components, and e_{1t}^d and e_{2t} represent the remaining iid unobserved determinants.

Assuming that e_{1t}^d is serially uncorrelated and Type-I Extreme Value distributed, the child care and maternal employment choice probabilities, conditional on the unobserved heterogeneity components (μ and ν_t), can be written (in log odds) as

$$\ln\left[\frac{\Pr(D_t = d|\mu_1, \nu_{1t})}{\Pr(D_t = 0|\mu_1, \nu_{1t})}\right] = \gamma_{0d} + \gamma_{1d}B_t + \gamma_{2d}X_t + \gamma_{3d}P_t + \gamma_{4d}Z_t + \mu_1^d + \nu_{1t}^d \quad d = 1, ..., 5. \tag{1.12}$$

For ease of description, I assume for now that body mass status is a dichotomous specification and the health production function conditional on the unobserved heterogeneity components (μ and ν_t) can be expressed as

$$\ln\left[\frac{\Pr(B_{t+1} = 1|\mu_2, \nu_{2t})}{\Pr(B_{t+1} = 0|\mu_2, \nu_{2t})}\right] = \beta_0 + \beta_1 B_t + \beta_2 D_t + \beta_3 B_t D_t + \beta_4 X_t + \beta_5 P_t + \mu_2 + \nu_{2t}. \tag{1.13}$$

I examine three different specifications of the dependent variable in equation 1.13 in estimation. First, I consider health status (B_t) as simply being measured by a child's Body Mass Index (BMI) percentile-for-age-and-sex, which is a continuous measure of health. Second, I dichotomize health where I define a child to be overweight or obese when his BMI-for-age-and-sex-percentile is above a given threshold (specifics of these body mass measures are discussed in Section 1.5.1 and Appendix A.4). The empirical specification includes an interaction between the employment and child care decision (D_t) and body mass status (B_t) that allows the effects of the mother's choices to have different effects for children of different body mass statuses.

The unconditional likelihood function for individual i is

$$\begin{aligned}
\mathrm{L}_i(\Theta, \psi, \pi) \quad = \quad & \sum_{k=1}^{K} \pi_k \Bigg\{ \Pr(B_1 = 1|\mu_{2k})^{B_{i1}} [1 - \Pr(B_1 = 1|\mu_{2k})]^{1-B_{i1}} \\
& \times \prod_{t=1}^{T} \sum_{\ell=1}^{L} \psi_\ell \Bigg[\prod_{d=0}^{5} \Pr(D_t = d|\mu_{1k}^d, \nu_{1t\ell}^d) \mathbf{1}[D_{it} = d] \\
& \Pr(B_{t+1} = 1|\mu_{2k}, \nu_{2t\ell})^{B_{it+1}} [1 - \Pr(B_{t+1} = 1|\mu_{2k}, \nu_{2t\ell})]^{1-B_{it+1}} \Bigg] \Bigg\}
\end{aligned} \tag{1.14}$$

where Θ is the vector of variables in the model that are to be estimated.

The distribution of the time-invariant heterogeneity (μ) is given by

$$\pi_k = \Pr(\mu_1^0 = \mu_{1k}^0, ..., \mu_1^5 = \mu_{1k}^5, \mu_2 = \mu_{2k}) \qquad k = 1, ..., K \tag{1.15}$$

where K is the number of time-invariant mass points and $\sum_{k=1}^{K} \pi_k$=1. The distribution of the time-varying heterogeneity (ν_t) is given by

$$\psi_\ell = \Pr(\nu_{1t}^0 = \nu_{1t\ell}^0, ..., \nu_{1t}^5 = \nu_{1t\ell}^5, \nu_{2t} = \nu_{2t\ell}) \qquad \ell = 1, ..., L, \forall t \tag{1.16}$$

where L is the number of time-varying mass points and $\sum_{\ell=1}^{L} \psi_\ell$=1.

Due to the dynamic nature of the model, health at the beginning of a period (B_t) explains health next time period ($t + 1$) and the joint employment and child care decisions. This relationship is true each period, including when individuals are first observed in the data. However, B_1 cannot be modeled as described above because behavior in previous periods (i.e., B_t and D_t at t=0) are unobserved. Therefore, I explain variations in the initial health state using a reduced form equation, expressed as

$$\ln \left[\frac{\Pr(B_1 = 1|\mu_2)}{\Pr(B_1 = 0|\mu_2)} \right] = \delta_0 + \delta_1 X_1 + \delta_2 Z_1 + \mu_2. \tag{1.17}$$

where Z_1 includes variables necessary for identification that are excluded from the subsequent dynamic equations. The time-invariant heterogeneity component (μ_2), that affects all subsequent body mass outcomes, also enters into this equation. The initial condition equation is jointly estimated with the health production and joint employment and child care decision equations.

1.4.3 Identification

Identification of the joint employment and child care demand equation requires that there be exogenous variables correlated with the joint decision, but uncorrelated with the error term in the body mass status equation conditional on the unobserved individual heterogeneity. The theoretical model implies that the joint decision is identified by time-varying county- and state-level variables ($Z_t = [W_t, P_t^c]$) that explain the distribution of wages and child care prices. Therefore, I exploit the availability of residential zip codes in the restricted-use data and match each child with community-level identifiers, listed in Table 1.

These identifying variables include: county-level poverty and unemployment rates, county-level median income, high school and college completion rates for a given state, benefit levels from the Temporary Assistance for Needy Families (TANF) program for a family of four, and mandatory job search requirements for TANF recipients to capture wages (W_t); and county-level mean wage of child care workers, total number of child care facilities (group home and regulated child care) per 1,000 people in a state, and state-level licensing requirements to capture child care prices (P_t^c). Mothers may be less inclined to leave a full-time employment position under poor market conditions (captured by poverty and unemployment rates, and median income). Further, stricter welfare rules may make mothers more likely to work. Lastly, the number of child care facilities, stringency of licensing requirements for child care centers, and the mean wage of child care workers may reflect the price of child care and the likelihood of child care usage.

Initial body weight status is identified by county- and state-level variables, such as price of food, availability of restaurants and fitness centers, and child care workers' wages, from the corresponding year, as well as the child's birth weight (in kilograms). In addition to the county- and state-level characteristics, all lagged exogenous variables and the nonlinearity of the model provide additional identification in this system of dynamic equations (Bhargava and Sargan, 1983).

In Tables A.1 to A.3, I report coefficients from the joint employment and child care decision equation with obese, overweight, and BMI-percentile as the outcomes, respectively. The last two rows of these tables display likelihood ratio statistics from tests of joint significance and over-identification. Although, in the three models, several of the identifying variables are individually insignificant, tests of joint significance indicate that the variables are significantly different from zero. In addition, the tests of over-identification provide further evidence of the validity of these instruments since they are jointly insignificant in the body mass status equation.[9] In Table A.4, I report coefficient estimates from the initial condition equations. One of the key identification variables in this equation, child's birth weight (in kilograms), is found to be highly significant in the initial body mass equation and insignificant in subsequent body mass equations conditional on body mass entering the period.

1.5 Data

In this analysis, I use longitudinal data from the restricted use version of the Early Childhood Longitudinal Study, Kindergarten Class of 1998-1999 (ECLS-K). The ECLS-K has followed a nationally representative sample of 21,409 kindergartners since the fall of 1998. During the first year of data collection, surveys were conducted in the fall and the spring of the 1998-1999 school year when the children were in kindergarten (waves 1 and 2, respectively). Follow-up surveys were conducted in the fall and spring of 1999-2000 (waves 3 and 4, respectively), when most of the children were enrolled in the first grade; spring of 2002 (wave 5), when most of the children were enrolled in the third grade; and spring of 2004 (wave 6), when most of the children were enrolled in the fifth grade. Detailed information on the child's emotional, cognitive, and physiological well-being and on his/her home and school environments were collected from the child, and the child's parents and school teachers. Furthermore, key county-, metropolitan area-, and state-level variables can be merged with each individual using the restricted use data

[9] A more detailed discussion regarding identification is available in Appendix A.3.

(available through a contract with the U.S Department of Education), which contains home and school zip codes of the children. For this paper, I focus on data from three survey years (waves 4, 5, and 6) in which key variables required for regression analysis are available.[10]

1.5.1 Description of Dependent Variables

Using data from the parent/guardian interview, I construct body mass status measures for each child. In particular, I use Body Mass Index (BMI), measured as a ratio of weight in kilograms over height in meters squared, to analyze obesity and overweight.[11] An overweight adult is defined as having a BMI greater than 25, an obese adult a BMI greater than 30, and a morbidly obese adult a BMI greater than 35. Children (ages 2-20) however, are classified as being overweight or obese using growth charts available from the National Center for Health Statistics (NCHS) which uses data collected in 1977 as baseline measurements. Following the CDC's guidelines, children's BMIs are compared to the growth chart's baseline measurements and classified as overweight if their age- and sex-specific BMIs exceed the 85th percentile and obese if greater than the 95th percentile.[12]

In Figure 1.1, I present shifts over time in sex-and-age specific BMI by comparing the 50th and 95th percentiles from two data sources: NHANES-I (data from 1977 that were used to develop the growth charts) and ECLS-K. The figures demonstrate that between the periods in which the two surveys were conducted, BMI shifted upward at the 50th and 95th percentile for all age groups and sexes. However, the BMI increase was markedly greater at the 95th

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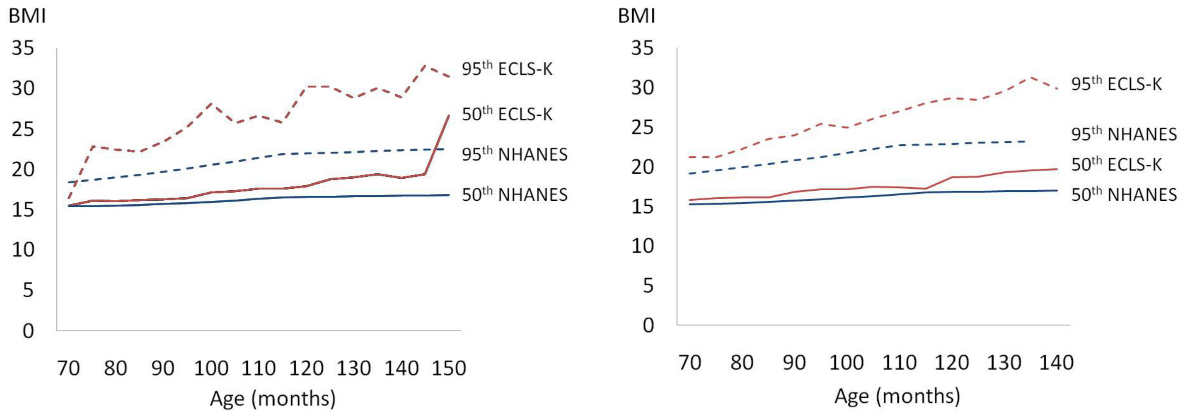
[10] A description of the endogenous (O_t, D_t) and exogenous (X_t) variables are available in Table 1.2. A detailed explanation of how the variables were constructed is available in Appendix A.4.

[11] The best measure of one's obesity/overweight status has yet to be determined and some researchers have suggested the use of waist-to-hip ratios or skinfold measurements as alternatives to determining obesity status. Nevertheless, I use BMI in this analysis because: (1) it is a standard measure used by other researchers which allows for easier comparison of my results and (2) weight and height measurements are collected in my data and allow for determination of body mass status. However, this does not imply that BMI is the most accurate measure of determining obesity status. In a recent paper by Burkhauser and Cawley (2008), the authors examine the relationship between BMI and other measures of fatness (e.g., Total Body Fat and Percent Body Fat). They find weak correlations between BMI and the alternative measures of fatness; for instance, the gap in obesity between white and African American males increases substantially when body fat percentages are used instead of BMI. Thus, readers should be aware that results may be sensitive to the definition of obesity and overweight.

[12] The CDC alternatively refers to having a BMI greater than the 85th percentile as "at-risk-of-overweight"and greater than the 95th percentile as "overweight". In this paper, I refer to being at-risk-of-overweight as overweight and overweight as obese for simplicity. A more detailed description of BMI is available in Appendix A.4



(a) Male (b) Female

Figure 1.2: Comparison of Body Mass Index at the 50th and 95th percentiles: NHANES vs ECLS-K

percentile, where BMI increased by around 3-5 kg/m^2, than at the 50th, where the increase was more modest at around 1-2 kg/m^2. This suggests that the growth in BMI has been greater at the right tail of the BMI distribution.

Variables of key interest in my analysis include the mother's employment hours and the child's time spent in child care. The survey collects information regarding the mother's weekly employment hours, which I divide into three categories: less than or equal to 8 hours per week, greater than 8 and less than or equal to 35 hours per week, and greater than 35 hours per week. The number of hours worked were divided into three categories to capture differing effects by work intensities.

Child care can be received either regularly (defined as care received more than once a week) or irregularly (defined as care received only once a week) and this distinction is made in the data. Given that a child receives child care on a regular basis, the number of child care hours can be divided into hours spent in informal care with a relative, such as with grandparents or siblings; informal child care with a non-relative, such as a babysitter; and formal child care, which is care received in a child care center. Using this information, I sum up the hours spent in the three types of child care settings and construct a child care indicator for whether child care was used more than five hours per week.

In Table 1.3, where I report the percentage of children from my sample in alternative combinations of employment and child care hours, I find that around 22% of the sample is employed more than 35 hours of work per week and uses more than or equal to 5 hours of child care per week. Unsurprisingly, the percentage of individuals using more than 5 hours of child care per week increases as the number of employment hours increase. Around 22% of individuals working full-time however, do not use child care. The only significant difference between those using and not using child care (while working full-time) was that mothers were more likely to be married and slightly less likely to be in the lowest income bracket (less than $25,000 per year) if they were not using child care.[13] The higher rate of married women may indicate that mothers who do not use child care, while working full-time, have husbands that coordinate with them to drop off and/or pick up children. Further, the lower percentage of individuals in the lowest income group may suggest that higher income households may have more flexible jobs (e.g., working from home) that allow them to not have to use child care. One other possibility, that cannot be tested from the available data, is that these children with full-time working mothers are staying at home by themselves (either before- or after-school), while their mothers work.

In Table 1.4, I present percentages of overweight (> 85th percentile-for-age-and-sex) and obese (> 95th percentile-for-age-and-sex) children, and their average BMI-percentiles by weekly hours of maternal employment and child care. The table indicates that as employment hours increase, the percentage of overweight (obese) children changes from 39.2% (14.5%) to 34.6% (18.5%). However, for children using child care, increases in maternal employment decrease the percentage of children that are obese from 22.2% to 18.3%. These simple statistics therefore suggest that failure to control for child care, when analyzing the impact of mothers' employment on children's health outcomes, can potentially produce misleading correlations.

1.5.2 Description of Explanatory Variables

The ECLS-K collects extensive background information for each child respondent. From this information, I construct child and mother characteristics that explain the outcomes of interest.

[13]Summary statistics comparing these two groups is available in Table A.7

Table 1.5 provides summary statistics. Also included in the maternal employment and child care demand and health production equations are the price and availability of food and activities. Despite being unable to observe individual-specific food and activity prices, I am able to exploit data on state-level fast food and full service restaurant prices and county-level numbers of supermarkets, convenience stores, fitness centers, and fast food and full service restaurants. Average price of fast food and full service restaurant meals were collected from the *Census of Retail Trade* 1987, 1992, 1997, and 2002 (Bureau of the Census), which defines fast food restaurants as establishments that sell primarily fast food type meals (burgers, pizza, etc.) and full service restaurants as establishments with menus, servers, and proper seating.[14] In addition, the *Census of Retail Trade* records data on the number of establishments whose average cost of a meal falls within price categories of: less than $2, 2-4.99, 5-6.99, 7-9.99, 10.00-14.99, 15.00-19.99, 20.00-29.99, and greater than 30, by state. To estimate the average prices of fast food and full service restaurant meals in a particular state, I take the midpoint of each price category, except for the less than $2 and more than $30 categories to which I assign a value of $1.50 and $45, respectively and then take a weighted average (weighted by the number of establishments in each price range). Since these data are only collected every five years (in years ending in a 7 or 2), I interpolate and extrapolate the missing years using a time trend of prices by state. All prices are then converted to 1982-1984 dollars using the Consumer Price Index.

Data on the number of establishments in a county were obtained from the US Census Bureau's County Business Patterns (CBP) data which evaluates the number of establishments of several hundred industries in a particular geographic area (i.e., zip code, county, or state). In this analysis I use establishment numbers of supermarkets, convenience stores, fitness centers, and fast food and full service restaurants in a county and standardize these numbers to the total number of establishments per 1,000 people in a given geographical area.

Of the 21,409 children who were surveyed in the base year, key variables (i.e., employment,

[14] It is unclear whether one type of restaurant serves healthier meals than another. For instance, full-service restaurants and fast food restaurants often serve similar types of foods (e.g., pizzas, burgers) where the only difference is how the meal is presented and sold. Therefore it should not be assumed that individuals consume less calories or eat healthier meals at full service restaurants.

child care, obesity, and explanatory variables) are missing during certain survey periods. Therefore, I restrict my sample to those individuals with information available in waves 4, 5, and 6. My final sample is comprised of 18,990 observations (6,330 individuals per wave × 3 waves).[15]

1.6 Results

1.6.1 Estimation Results

I begin this section by showing marginal effects (i.e., the short run effects) of the employment and child care alternatives on children's body mass statuses.[16] I compare results that do not control for unobservable characteristics that are potentially correlated with the employment and child care decision and child health to those that do. In Tables 1.6, 1.7, and 1.8, I present marginal effects of different employment and child care alternatives on three different measures of body mass status: risk of being obese, risk of being overweight, and BMI-percentile-for-sex-and age, respectively.[17] The reported values are marginal effects averaged over all observations.

Results not controlling for unobserved heterogeneity

Models 1a, 1b, and 1c contain results from three specifications of the model that ignore the possible endogeneity of the employment and child care decision. Model 1a estimates body mass status as a function of employment and child care alternatives only, Model 1b then adds controls for exogenous mother, father, child, and community characteristics (X_t, P_t), and finally Model 1c adds health status entering the period (lagged health or B_t) into the specification. Standard errors are non-parametrically bootstrapped with 200 draws.

The first column shows that each combination of employment and child care, except for part-time work and not using child care, noticeably increases risk of obesity and being overweight,

[15] A discussion of attrition bias and the test results are available in Appendix A.6.

[16] A more detailed explanation of how the marginal effects were estimated is available in Appendix A.8. Appendix A.7 details how interaction effects in non-linear models are estimated.

[17] Coefficient estimates from the model are available in Appendix A.11.

and BMI-percentile compared to not working and not using any child care. For instance, full-time work, regardless of child care, increases the risk of being obese by more than 4 percentage points and the risk of being overweight by almost 6 percentage points. Similarly, full-time work increases BMI-percentile by around 4 percentile points. The addition of covariates in the second column slightly reduce the risk of obesity and being overweight, and BMI-percentile for those employed full-time. The addition of health entering the period in Model 1c decreases the effect of alternative employment and child care combinations on all three body mass measures indicating that some of the effects of employment and child care in the past may be captured by this term. Compared to not working and not using child care, working full-time and using child care increases the risk of obesity by 1.1 percentage points, increases the risk of being overweight by 0.7 percentage points, and increases BMI-percentile by 0.8 percentile points. It must be noted, however, that the results in the first three columns suffer from endogeneity bias since I do not control for potential time-invariant and time-varying unobserved heterogeneity. Inclusion of the exogenous variables (i.e., Models 1b and 1c) into the models suggest that if there are unobservable variables influencing the employment and child care decision, as well as the body mass status outcome, the direction of the bias tends to be an upward bias.

Results controlling for permanent unobserved heterogeneity

Models 2a, 2b, and 2c have similar specifications as those in models 1a, 1b, and 1c, but adds a fixed individual effect to control for permanent individual unobservables that may possibility be correlated with the employment and child care decision, and body mass outcome. Standard errors are non-parametrically bootstrapped with 200 draws.

Controlling for potential time-invariant unobserved heterogeneity significantly alters the results (models 2a-2c). Work of any type (part-time or full-time) now has a negative and mainly insignificant effect on body mass status. When mothers work full-time and do not use child care, the risk of obesity decreases by 1.5 percentage points and decreases risk of being overweight by around 2 percentage points. These results provide evidence of potential time-invariant unobservable factors that may be correlated with both the employment and child care decision, and child health. Furthermore, the results also suggest that an upward endogeneity bias has made a difference and that the unobservable factors, that are fixed over time, may have confounded the relationship between employment and child care and child health.[18]

Results controlling for permanent and time-varying unobserved heterogeneity

Lastly in Model 3 (the preferred model) the joint employment and child care decision, body mass status, and initial health are estimated simultaneously using the semi-nonparametric estimation technique that allows for both permanent and time-varying individual unobservables. In Table 1.6, I present marginal effects of a joint estimation of an obesity outcome equation with the employment and child care alternative equations. The joint estimation amplifies the impact of alternative employment and child care combinations on body mass status (compared to Model 2) and reverses the sign in some cases (compared to Model 1). For instance, the impact of full-time employment and not using child care significantly decreases the risk of obesity by 2.4 percentage points. The addition of time-varying unobservables suggest that unobservable heterogeneity factors, such as children's or mothers' unobserved health status (e.g., mother's depression), which may have deteriorated over time may increase the probability that child care is used and also increase the probability that a child is in poor health (as measured by a high risk of being obese).

A similar pattern is observed in Table 1.7, where I present joint estimation results with overweight as the body mass outcome. However, the negative impact of full-time employment on children's risk of being overweight is not as large as for the risk of being obese. Interestingly, the impact of full-time employment without child care has a negative impact on the risk of being overweight, compared to a positive impact of full-time employment using child care (compared to not working and not using any child care). Lastly, in Table 1.8, full-time employment and child care have very little significant impact on children's BMI-percentile for sex and age. In all cases however, the impact of the employment and child care alternatives are all negative and the findings once again suggest that there are potential permanent and time-varying heterogeneity

[18] An upward bias due to permanent heterogeneity is consistent with the story that mothers who place a heavier priority on work compared to their children's health are more likely to work and also more likely to have a child that is unhealthy.

factors influencing the employment and child care choices and children's health.

1.6.2 Simulation Results

The marginal effects discussed in the previous section are short-run (one period) effects of employment and child care alternatives on child's body mass status. The theory suggests that body mass status is directly influenced by body mass status entering the period and employment and child care decisions. These employment and child care decisions are directly influenced by body mass status entering the period and indirectly influenced by employment and child care decisions made in the previous period through body mass status entering the period. Due to the dynamic nature of the model, simulations best capture the long-run impact of the employment and child care alternatives on a child's health. Therefore, I simulate the three body mass outcomes of children over three periods (i.e., first, third, and fifth grade) under the six possible employment and child care combinations. I begin the simulation by generating 10 replications of each individual and allow each replication one draw from the permanent individual heterogeneity distribution, estimated coefficients (which are perturbed by an error term drawn from the estimated covariance matrix), and draws every period from the time-varying heterogeneity distribution. Using observed body mass status in kindergarten (rather than predicting the initial body mass status from the estimated initial body mass equation), employment and child care is simulated in first grade. Given these simulated choices, I then update the child's body mass status at the end of the period. This updating process is repeated for the third and fifth grades.

Long run effects with and without unobserved heterogeneity

In Table 1.9, I report five year simulations of the predicted risk of obesity and of being obese, and BMI-percentile-for-sex-and-age under the six employment and child care alternatives. I compare the simulated effects across three alternative models: Model 1c that does not control for potential unobservables; Model 2c, that controls for permanent heterogeneity; and Model 3, that controls for both permanent and time-varying heterogeneity. The table shows that for full-time employment (regardless of child care) failure to control for unobservables result in an overbias in the impact of employment and child care on the risk of being obese and on BMI-percentile-for-sex-and-age. However, the bias is not as strong on the risk of being overweight. The reported simulation results suggest that both permanent and time-varying heterogeneity have made a difference.

In Tables 1.10 and 1.11, I present five year simulation effects of employment and child care on body mass status. Table 1.10 shows the effect on body mass status compared to not working and not using child care and Table 1.11 compared to full-time work and not using child care. Table 1.10 shows that full-time employment, regardless of child care, decreases the risk that a child is obese compared to if the mother did not work and did not use child care. Specifically, full-time employment and no child care decreases obesity risk by 7 percentage points (from 19.8% to 12.8%) and full-time employment with child care decreases obesity risk by 4 percentage points (from 19.8% to 15.8%).

In contrast to the results found in Table 1.10, the effect of using child care seems to have detrimental effects on children's health (see Table 1.11). That is, using child care increases the risk that a child is obese by 3 percentage points (from 12.8% to 15.8%) and increases the risk that a child is overweight by 6 percentage points (from 33% to 39%) if mothers work full-time. The effect of employment and child care alternatives on BMI-percentile are insignificant. This finding may suggest that child care, for full-time workers, is more detrimental to children at the right tails rather than at the mean of the BMI distribution (i.e., the effect if greater for children with high BMI-percentiles).

Differences in the long run effect by initial body mass status

In Table 1.12, I report the predicted risk of being obese and overweight, by the child's body mass status in kindergarten. Specifically, the long run effects of the alternatives are reported for children who were obese ($\geq$ 95th percentile), overweight but not obese ($\geq$ 85th percentile, but $<$ 95th percentile), and normal weight ($<$ 85th percentile). I find (compared to not working and not using child care) full-time employment with no child care decreases obesity risk by: 12.0% (from 58.2% to 51.2%) for children who were obese in kindergarten; 46.7% (from 16.2% to 8.7%) for children who were overweight in kindergarten; and 46.9% (from 14.7% to 7.8%) for children who were normal weight in kindergarten. In addition, I find (compared to not working and not using child care) full-time employment with child care: increases obesity risk by 0.3% (58.2% to 58.4%) for children that were obese in kindergarten; decreases obesity risk by 30.6% (from 16.2% to 11.3% and 14.7% to 10.2%, respectively) for children that were overweight and normal weight in kindergarten.

Interestingly, I find (compared to not working and not using child care) full-time employment with no child care *increases* overweight risk by 13.2% (from 62.8% to 71.1%) if the child were obese in kindergarten and by 14.5% (from 59.4% to 68.0%) if the child were overweight in kindergarten, whereas for children who were normal weight, there is a decrease in overweight risk by 46.9% (from 26.2% to 20.7%). The increase in the risk that the child is overweight in the fifth grade, given that they were obese or overweight in kindergarten, is more pronounced for mothers who work full-time and use child care (compared to if they neither worked nor used child care).

Overall, the findings suggest that using child care (for full-time workers) is detrimental (i.e., increases the risk of obesity and being overweight) to the body mass status of children, regardless of their body mass history whereas the effect of full-time employment (compared to no work) is somewhat mixed. The findings additionally suggest that the effect differs along the BMI-distribution and that the effect of such alternatives differ by the child's body mass status in kindergarten.

1.6.3 Estimates for Subgroups

In this section, I analyze whether there are significant differences in the impact of employment and child care alternatives on body mass status by gender or by race. Gender differences may be observed if mothers' absence from the home, for example, has a greater impact on girls who may be more likely to emulate mothers' behaviors (e.g., eating or activity behaviors) than boys. Similarly, the detrimental impact of attending child care may be greater for girls than for boys if boys are more likely to engage in rigorous activities with their peers.

In tables 1.13 and 1.14, I present simple summary statistics of body mass status (obese, overweight, and BMI-percentile) by gender and race respectively, for alternative employment and child care choices. Differences between subgroups are also reported in theses tables. In Table 1.12, I show, regardless of the employment and child care alternative, that males are more likely than females to be obese (overweight) and that these differences are statistically significant, overall.

In Table 1.13 I show, holding child care constant at no child care, that going from no work to full-time employment increases obesity risk by 28.4% (from 16.5% to 21.2%) for males and 37.0% (from 11.7% to 16.1%) for females. Moving from no work and no child care to full-time work *with* child care, on the other hand, increases the risk that a male child is obese by 20.7% (from 16.5% to 19.9%) and the risk that a female child is obese by 41.5% (from 11.7% to 16.7%). Holding employment constant at full-time employment, using child care decreases the risk that a male child is obese by 6.0% (from 21.2% to 19.9%) but increases the risk that a female child is obese by 3.2% (from 16.1% to 16.7%). Similar patterns are observed for the risk of being overweight.

In Table 1.14, I present simple summary statistics by black, Hispanic, and non-black and non-Hispanic subgroups.[19] Blacks and Hispanics are more likely to be obese and overweight in all employment and child care categories compared to their non-black, non-Hispanic counterparts. Furthermore, these differences are statistically significant, overall. Going from no work and no child care to full-time employment and using child care increases obesity risk by 41.2% (from 11.7% to 16.5%) for the non-black and non-Hispanic group, 4.7% for blacks (from 21.0% to 22.0%), and 12.6% for Hispanics (from 20.6% to 23.2%).

The results presented in Tables 1.13 and 1.14 do not control for variables (both observable and unobservable) that may influence the employment and child care decision, and child health. Thus estimations were conducted controlling for such characteristics. The results (not shown in this paper) revealed very little differences by gender and by race, after controlling for observable characteristics. Furthermore, fixed effects estimations that controlled for unobserved permanent heterogeneity showed that there were no differences in the impact of employment and child care

[19] Individuals in my sample are categorized into one of three major race categories: (1) black, (2) Hispanic, and (3) non-black, non-Hispanic. Individuals in the third category are not necessarily white (they could be Asian, for example).

on children's health.

1.7 Discussion and Summary

Findings from previous literature, that mainly examined correlations between maternal employment and children's obesity risk, suggest that there is a detrimental effect of mothers' work on children's health. Through such findings researchers posit that this is a result of working mothers being unable to cook healthy (i.e., low caloric) meals and their inability to monitor their children's daily activities, resulting in more time spent in sedentary activities. However, in this analysis I find that women's labor force participation may not have been the main cause of the increase in obesity risk, but rather child care usage, that is strongly intertwined with women's employment decisions.

I find that full-time work decreases the risk of obesity and hypothesize three main mechanisms which may explain this finding. First, women who are employed may have an increase in income, that may allow them to purchase healthier meals and more quality activities for their children. Second, due to the nature of my data, my analysis focuses on children who attend school for the majority of the day. Thus, employed mothers may be working while the child is at school, thereby having very little impact of the actual amount the children spend without their mothers. Furthermore fathers, who I do not discuss in very great detail in this paper, may be pitching in to spend more time with their children. Lastly, mothers who work may experience greater levels of self-esteem that may translate into better behaviors for themselves and their children in the home. Including a control for the mother's income would allow for the effect of mothers' income on children's body mass status to be differentiated from the effect of their time away from home. Unfortunately, I was unable to address this issue due to data limitations. However, when I conducted analyses controlling for total household income, the results were slightly smaller in magnitude but, I continued to find the reduction in the risk of obesity and overweight for mothers working full-time to be true.

On the other hand, I find that child care usage, defined in this analysis as informal child care with a relative, informal child care with a non-relative, and formal child care, has a detrimental effect on children's health. Since I do not differentiate between child care modes and because I am unable to observe the actual skills and actions of child care providers, I again posit some possible explanations of this finding. First, skills of babysitters or relatives (i.e., informal child care givers) are often unknown. Although parents will potentially choose child care givers based on the desire that their children are kept safe, child care givers may have very little information about or motivation to encourage nutrition or physical activity choices that may benefit children. Second, even in formal child care settings licensing requirements for these centers are weak at best. Again, these child care workers may be working with the best interest of the children at heart, but may simply have inadequate information or motivation to properly address children's physical health needs.

This study contributes three important ideas. First, this analysis goes beyond the current research that looks only at maternal employment to examine the joint impact of employment and child care decisions on children's body mass status. Second, I examine the dynamic behavior of individuals such that the effect of employment and child care decisions influence health outcomes today, but also decisions and health in future periods. As such, I am able to provide short-run and long-run estimates that capture the dynamic effect of employment and child child care. Finally, I provide evidence that failure to capture both permanent and time-varying heterogeneity can result in estimates that overemphasize the detrimental impact of employment and child care on children's body mass status.

In general, these findings shed more light on how changes in women's labor force participation may have affected children's obesity risk. Unlike the popular notion that mothers' attachment to the labor force may have been a contributing factor in the childhood obesity epidemic, this paper examines child care and the possible implications associated with its usage. This work however, is limited in that I am unable to observe specific activities and food intake of children; therefore, I am unable to observe the mechanisms through which employment and child care may affect children's health. For instance, having a food or time diary of children's behaviors while in child care may provide a greater understanding of whether the detrimental impact of child care arises from a lack of vigorous exercise, increased consumption of poor quality foods, or both. The analysis presented suggests that a greater awareness for better monitoring and regulations of child care (both informal and formal) may be necessary. Future analysis investigating the mechanisms through which employment and child care decisions affect health may better inform policymakers of how to adequately address the childhood obesity epidemic.

Table 1.1: Definition and Summary Statistics of Instruments ($Z_t = [W_t, P_t^c]$)

Variable	Description	Variation	Mean	Standard Deviation
Employment Related Variables (W_t)				
Median Income	Median household income (1982-1984 $s)	county, time	25,789.57	61,600.31
% in Poverty	Percent of people in poverty	county, time	11.40	4.56
% Unemployed	Percent of people unemployed	county, time	4.82	1.71
% High School Degree	Percent of people with high school degree	state, time	84.19	3.82
% College Degree	Percent of people with college degree	state, time	26.34	4.10
TANF Benefits	Maximum monthly TANF benefit for a family of three (1982-1984 $s)	state, time	236.19	87.06
Mandatory Job Search	Indicator of mandatory job search at time of TANF application	state, time	0.30	0.46
Child Care Related Variables (P_t^c)				
Mean Wage	Mean wage of child care workers (1982-1984 $s)	MSA, time	4.52	53.87
# of Centers	Number of regulated child care centers per 1,000 people	state, time	0.40	0.12
# of Family and Group Centers	Total number of family and group child care centers per 1,000 people	state, time	1.12	0.62
Center License	Indicator of required licensing for child care centers	state, time	0.31	0.46
Family License	Indicator of required licensing for family child care arrangements	state, time	0.46	0.50
Group License	Indicator of required licensing for group child care arrangements	state, time	0.76	0.43
Initial Health				
Birth Weight	Child's birth weight in kilograms	individual	3.36	0.62

Sources:
(1) Median Income, % in Poverty, % High School Degree, % College Degree, and Mean Wage: U.S Census Bureau
(2) % Unemployed: Bureau of Labor Statistics
(3) TANF Benefits and Mandatory Job Search: *Welfare Rules Databook* (Urban Institute, 2000, 2002, 2004)
(4) # of Centers, Center License, Family License, and Group Family License: *Child Care Licensing Study* (The Children's Foundation, 2000-2005)

Table 1.2: Definition of Dependent and Explanatory Variables

Variable	Description
Dependent Variables (B_t, H_t, C_t)	
BMI Percentile	Age and sex specific Body Mass Index percentile
Obese	Indicator equal to 1 if child's BMI is greater than the 95th percentile for age and sex
Overweight	Indicator equal to 1 if child's BMI is greater than the 85th percentile for age and sex
Employment	
Not working	Dichotomous variable equal to 1 if weekly employment hours is ≥ 0 & ≤ 8
Part-time	Dichotomous variable equal to 1 if weekly employment hours is > 8 & ≤ 35
Full-time	Dichotomous variable equal to 1 if weekly employment hours is > 35
Child Care	Dichotomous variable equal to 1 if weekly hours in child care is ≥ 5
Child Characteristics (X_t)	
Age	Age of child at date of interview in years
Male	Dichotomous variable equal to 1 if child is male
Black	Dichotomous variable equal to 1 if child is black
Hispanic	Dichotomous variable equal to 1 if child is Hispanic
Siblings	Number of siblings in the household

Table 1.2 (continued)

Variable	Description
Mother and Father Characteristics (X_t)	
Age	Age of mother (father) at ate of interview in years
Education	
< High School	Dichotomous variable equal to 1 if mother (father) has < a HS education
High School	Dichotomous variable equal to 1 if mother (father) has a HS education (nothing beyond)
Some College	Dichotomous variable equal to 1 if mother (father) attended college but did not graduate
≥ College	Dichotomous variable equal to 1 if mother (father) has at least a college diploma
Prior Work	Dichotomous variable equal to 1 if mother worked before child entered kindergarten
Married	Indicator equal to 1 if mother is married
Food and Activity Price and Availability (P_t)	
Fast Food Price	Average price of food at fast food restaurants in the child's state of residence (1982-1984 $s)
Restaurant Price	Average price of food at full service restaurants in the child's state of residence (1982-1984 $s)
# of Limited Service Restaurants	Number of limited service restaurant establishments per 1,000 people in a county
# of Full Service Restaurants	Number of full service restaurant establishments per 1,000 people in a county
# of Supermarkets	Number of supermarket establishments per 1,000 people in a county
# of Convenience Stores	Number of convenience store establishments per 1,000 people in a county
# of Fitness Centers	Number of fitness center establishments per 1,000 people in a county

Table 1.3: Descriptive Statistics of Employment and Child Care Alternatives

	Employment alternatives			
	Not working	Part-time	Full-time	Overall
Child Care Alternatives				
Not using child care	27.2	21.4	22.3	70.9
Using child care	1.7	5.6	21.8	29.1
Overall	28.9	26.0	44.1	100.0

Note: These are percentages of the sample in alternative employment and child care categories.

Table 1.4: Descriptive Statistics of Body Mass Status by Employment and Child Care Alternatives

Body Mass Status	Not working	Part-time	Full-time	Overall
Obese (%)				
Not using child care	14.1	13.7	18.7	15.4
Using child care	22.1	16.4	18.3	18.1
Overall	14.5	14.3	18.5	16.2
Overweight (%)				
Not using child care	28.9	28.7	34.7	30.7
Using child care	33.9	32.3	34.5	34.0
Overall	39.2	29.4	34.6	31.6
BMI-Percentile				
Not using child care	60.9	61.2	65.2	62.4
Using child care	64.0	64.3	65.2	64.9
Overall	61.1	61.8	65.2	63.0

Table 1.5: Descriptive Statistics of Exogenous Variables

Variable	Mean	Standard Deviation
Child Characteristics (X_t)		
Age	9.23	1.66
Male	0.50	0.50
Black	0.09	0.29
Hispanic	0.17	0.37
Siblings	1.54	1.10
Household Income		
$0-25,000	0.18	0.38
$25,000-50,000	0.28	0.45
$50,000-75,000	0.21	0.41
>$75,000	0.33	0.47
Mother Characteristics (X_t)		
Age	38.29	6.43
Education		
< High School	0.09	0.29
High School	0.24	0.43
Some College	0.35	0.48
≥ College	0.32	0.47
Married	0.81	0.39
Father Characteristics (X_t)		
Age	40.83	7.01
Education		
< High School	0.10	0.30
High School	0.25	0.43
Some College	0.27	0.45
≥ College	0.38	0.48
Food and Activity Price and Availability (P_t)		
Fast Food Price	3.45	0.24
Restaurant Price	6.39	1.22
# of Limited Service Restaurants	0.14	0.16
# of Full Service Restaurants	0.70	0.25
# of Supermarkets	0.08	0.07
# of Convenience Stores	0.11	0.06
# of Fitness Centers	0.10	0.04
Sample Size (person-year observations)	18,990	

Table 1.6: Marginal Effect of Maternal Employment and Child Care Alternatives on the Risk of Being Obese

	Exogenous			Individual Fixed Effect			Joint
Employment and child care alternatives	Model 1a	Model 1b	Model 1c	Model 2a	Model 2b	Model 2c	Model 3
No work, no child care	Omitted Category						
No work, using child care	0.087 ***	0.042 *	0.004	0.004	0.003	0.003	0.030
	(0.025)	(0.023)	(0.013)	(0.019)	(0.018)	(0.019)	(0.027)
Part-time, no child care	-0.005	0.001	-0.001	0.002	-0.010	-0.010	-0.017 *
	(0.008)	(0.008)	(0.005)	(0.008)	(0.007)	(0.008)	(0.011)
Part-time, using child care	0.025 **	0.025 **	0.009	-0.003	0.001	0.001	-0.001
	(0.013)	(0.013)	(0.009)	(0.013)	(0.012)	(0.011)	(0.015)
Full-time, no child care	0.049 ***	0.032 ***	0.003	0.001	-0.016 *	-0.015 *	-0.024 **
	(0.008)	(0.009)	(0.005)	(0.009)	(0.009)	(0.009)	(0.012)
Full-time, using child care	0.044 ***	0.031 ***	0.011 *	-0.009	-0.009	-0.009	-0.012
	(0.008)	(0.009)	(0.006)	(0.010)	(0.010)	(0.010)	(0.015)
Controls for:							
Exogenous characteristics	No	Yes	Yes	No	Yes	Yes	Yes
Lagged health	No	No	Yes	No	No	Yes	Yes

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for Models 1 and 2, and parametrically using 200 repetitions for Model 3. Model 3 is estimated using 9 permanent and 4 time-varying heterogeneity mass points.
*** indicates significance at 1%, ** 5%, and * 10%. Coefficient from estimation available in Appendix A.1 and A.10.

Table 1.7: Marginal Effect of Maternal Employment and Child Care Alternatives on the Risk of Being Overweight

	Exogenous			Individual Fixed Effect			Joint
Employment and child care alternatives	Model 1a	Model 1b	Model 1c	Model 2a	Model 2b	Model 2c	Model 3
No work, no child care	Omitted Category						
No work, using child care	0.053 *	0.006	-0.017	-0.005	-0.008	-0.009	0.001
	(0.030)	(0.027)	(0.015)	(0.024)	(0.020)	(0.023)	(0.033)
Part-time, no child care	-0.003	0.003	-0.003	-0.002	-0.023 **	-0.022 **	-0.006
	(0.010)	(0.010)	(0.007)	(0.010)	(0.010)	(0.011)	(0.012)
Part-time, using child care	0.035 **	0.035 **	0.002	-0.010	-0.006	-0.004	0.011
	(0.017)	(0.016)	(0.011)	(0.016)	(0.015)	(0.015)	(0.021)
Full-time, no child care	0.059 ***	0.037 ***	0.004	0.009	-0.020 *	-0.019	-0.007
	(0.010)	(0.011)	(0.007)	(0.012)	(0.011)	(0.012)	(0.017)
Full-time, using child care	0.057	0.042	0.015 **	-0.007	-0.009	-0.010	0.013
	(0.010)	(0.011)	(0.007)	(0.013)	(0.013)	(0.013)	(0.023)
Controls for:							
Exogenous characteristics	No	Yes	Yes	No	Yes	Yes	Yes
Lagged health	No	No	Yes	No	No	Yes	Yes

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for Models 1 and 2, and parametrically using 200 repetitions for Model 3. Model 3 is estimated using 6 permanent and 4 time-varying heterogeneity mass points.
*** indicates significance at 1%, ** 5%, and * 10%. Coefficient from estimation available in Appendix A.1 and A.10.

Table 1.8: Marginal Effect of Maternal Employment and Child Care Alternatives on BMI-Percentile-for-Sex-and-Age

	Exogenous			Individual Fixed Effect			Joint
Employment and child care alternatives	Model 1a	Model 1b	Model 1c	Model 2a	Model 2b	Model 2c	Model 3
No work, no child care				Omitted Category			
No work, using child care	3.043 *	0.190	-0.320	-0.036	-0.719	-0.041	-0.421
	(1.608)	(1.803)	(0.874)	(1.184)	(1.274)	(1.225)	(1.003)
Part-time, no child care	0.256	0.847	0.233	-0.035	-0.901 *	-0.887 *	-1.006
	(0.626)	(0.648)	(0.345)	(0.528)	(0.508)	(0.484)	(0.843)
Part-time, using child care	3.335 ***	3.218 ***	0.243	-1.044	-0.894	-0.925	-1.230
	(1.020)	(0.936)	(0.567)	(0.797)	(0.724)	(0.710)	(0.826)
Full-time, no child care	4.310 ***	3.274 ***	0.637 *	0.506	-0.697	-0.706	-0.933
	(0.575)	(0.641)	(0.361)	(0.632)	(0.575)	(0.560)	(1.258)
Full-time, using child care	4.238 ***	3.399 ***	0.785 **	-0.103	-0.203	-0.198	-0.575
	(0.598)	(0.648)	(0.385)	(0.612)	(0.619)	(0.632)	(0.804)
Controls for:							
Exogenous characteristics	No	Yes	Yes	No	Yes	Yes	Yes
Lagged health	No	No	Yes	No	No	Yes	Yes

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for Models 1 and 2, and parametrically using 200 repetitions for Model 3. Model 3 is estimated using 4 permanent and 3 time-varying heterogeneity mass points. *** indicates significance at 1%, ** 5%, and * 10%. Coefficient from estimation available in Table K1.

Table 1.9: Five Year Prediction of Body Mass Status by Employment and Child Care Alternatives

Employment and child care alternatives	Model 1c		Model 2c		Model 3	
Probability of Obese						
No work, no child care	18.56	(0.94)	20.29	(0.75)	19.80	(3.18)
No work, using child care	20.12	(3.03)	20.58	(1.43)	30.76	(10.87)
Part-time, no child care	18.48	(1.15)	19.37	(0.71)	14.52	(1.89)
Part-time, using child care	20.78	(2.00)	20.35	(1.02)	19.33	(3.11)
Full-time, no child care	19.18	(1.08)	18.68	(0.64)	12.80	(1.25)
Full-time, using child care	21.30	(1.04)	19.32	(0.75)	15.75	(1.97)
Probability of Overweight						
No work, no child care	35.77	(1.19)	37.93	(0.83)	35.09	(4.05)
No work, using child care	31.35	(3.33)	37.39	(1.85)	36.35	(11.17)
Part-time, no child care	35.16	(1.26)	35.62	(0.89)	33.44	(2.55)
Part-time, using child care	36.13	(2.22)	37.44	(1.26)	38.65	(4.28)
Full-time, no child care	36.76	(1.22)	36.03	(0.77)	33.09	(2.33)
Full-time, using child care	39.60	(1.40)	37.18	(0.97)	39.28	(3.73)
Predicted BMI						
No work, no child care	64.28	(0.57)	65.58	(0.43)	66.75	(1.64)
No work, using child care	63.47	(2.26)	65.52	(1.09)	65.72	(3.13)
Part-time, no child care	64.80	(0.69)	64.71	(0.45)	64.21	(0.90)
Part-time, using child care	60.81	(0.44)	60.23	(0.46)	63.65	(1.46)
Full-time, no child care	65.83	(0.66)	64.92	(0.44)	64.40	(1.71)
Full-time, using child care	66.22	(0.73)	65.40	(0.46)	65.30	(1.00)

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for Models 1 and 2, and parametrically using 200 repetitions for Model 3.

Table 1.10: Five Year Simulation Differences of Body Mass Status by Alternative Employment and Child Care

(compared to no work and no child care)

Employment and Child care Alternatives	Model 1c		Model 2c		Model 3	
Probability of Obese						
No work, using child care	1.552		0.290		10.959	
	(3.192)		(1.551)		(10.287)	
Part-time, no child care	-0.086		-0.924		-5.277	
	(1.453)		(0.716)		(3.318)	
Part-time, using child care	2.212		0.064		-0.465	
	(2.174)		(1.123)		(4.761)	
Full-time, no child care	0.611		-1.614	*	-7.002	***
	(1.476)		(0.887)		(3.768)	
Full-time, using child care	2.732	**	-0.970		-4.046	
	(1.331)		(0.964)		(4.639)	
Probability of Overweight						
No work, using child care	-4.416		-0.535		1.260	
	(3.607)		(1.910)		(11.378)	
Part-time, no child care	-0.605		-2.304	***	-1.652	
	(1.715)		(0.817)		(3.714)	
Part-time, using child care	0.362		-0.486		3.564	
	(2.553)		(1.156)		(6.488)	
Full-time, no child care	0.990		-1.897	**	-1.998	
	(1.656)		(0.934)		(5.490)	
Full-time, using child care	3.829	**	-0.742		4.197	
	(1.838)		(1.098)		(7.295)	
Predicted BMI						
No work, using child care	-0.806		-0.060		-1.031	
	(2.358)		(1.070)		(2.641)	
Part-time, no child care	0.518		-0.873	**	-2.540	
	(0.836)		(0.382)		(2.130)	
Part-time, using child care	0.650		-0.866		-3.105	
	(1.390)		(0.618)		(2.089)	
Full-time, no child care	1.553	*	-0.657		-2.354	
	(0.840)		(0.465)		(3.182)	
Full-time, using child care	1.939	**	-0.181		-1.450	
	(0.949)		(0.464)		(2.021)	

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for Models 1 and 2,and parametrically using 200 repetitions for Model 3. Coefficients from estimation are available in Table K1. *** indicates significance at 1%, ** 5%, and * 10%.

Table 1.11: Five Year Simulation Differences of Body Mass Status by Alternative Employment and Child Care

(compared to full-time work and no child care)

Employment and Child care Alternatives	Model 1c		Model 2c		Model 3	
Probability of Obese						
No work, no child care	-0.611		1.614	*	7.002	***
	(1.476)		(0.887)		(3.768)	
No work, using child care	0.941		1.904		17.960	***
	(3.251)		(1.540)		(11.152)	
Part-time, no child care	-0.698		0.690		1.724	
	(1.506)		(0.748)		(2.624)	
Part-time, using child care	1.601		1.678	*	6.536	**
	(2.262)		(1.069)		(3.380)	
Full-time, using child care	2.120		0.644		2.956	***
	(1.450)		(0.610)		(1.859)	
Probability of Overweight						
No work, no child care	-0.990		1.897	**	1.998	
	(1.656)		(0.934)		(5.490)	
No work, using child care	-5.406	*	1.362		3.258	
	(3.459)		(1.950)		(12.206)	
Part-time, no child care	-1.595		-0.406		0.346	
	(1.745)		(0.920)		(3.991)	
Part-time, using child care	-0.628		1.411		5.562	
	(2.545)		(1.273)		(5.177)	
Full-time, using child care	2.839	*	1.155		6.194	**
	(1.880)		(0.857)		(3.164)	
Predicted BMI						
No work, no child care	-1.553	*	0.657		2.354	
	(0.840)		(0.465)		(3.182)	
No work, using child care	-2.359		0.597		1.323	
	(2.331)		(1.057)		(4.240)	
Part-time, no child care	-1.035		-0.216		-0.186	
	(0.858)		(0.402)		(1.690)	
Part-time, using child care	-0.903		-0.209		-0.751	
	(1.455)		(0.638)		(2.525)	
Full-time, using child care	0.386		0.477		0.904	
	(0.935)		(0.402)		(1.983)	

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for Models 1 and 2,and parametrically using 200 repetitions for Model 3. Coefficients from estimation are available in Table K1. *** indicates significance at 1%, ** 5%, and * 10%.

Table 1.12: Five Year Prediction of Body Mass Status by Employment and Child Care Alternatives: Differences by Body Mass Status in Kindergarten

Employment and child care alternatives	Body Mass Status in Kindergarten					
	Obese		Overweight		Normal	
Probability of Obese						
No work, no child care	58.24	(6.30)	16.24	(3.44)	14.67	(3.10)
No work, using child care	77.92	(10.63)	26.65	(11.93)	24.42	(11.26)
Part-time, no child care	51.49	(6.25)	10.73	(1.83)	9.66	(1.62)
Part-time, using child care	57.64	(7.23)	15.75	(3.28)	14.23	(3.00)
Full-time, no child care	51.22	(4.70)	8.65	(1.10)	7.79	(1.01)
Full-time, using child care	58.44	(5.65)	11.29	(1.86)	10.16	(1.72)
Probability of Overweight						
No work, no child care	62.81	(5.51)	59.41	(5.78)	26.24	(3.75)
No work, using child care	77.00	(14.22)	74.58	(15.29)	22.88	(11.15)
Part-time, no child care	66.40	(3.84)	63.04	(4.00)	22.78	(2.43)
Part-time, using child care	70.27	(5.25)	67.25	(5.50)	28.39	(4.52)
Full-time, no child care	71.12	(3.86)	68.00	(4.08)	20.65	(2.10)
Full-time, using child care	74.67	(4.18)	71.93	(4.46)	27.68	(3.78)
Predicted BMI						
No work, no child care	89.22	(1.74)	83.90	(1.73)	60.07	(1.64)
No work, using child care	91.84	(3.89)	85.72	(3.62)	57.94	(3.26)
Part-time, no child care	87.47	(1.15)	81.98	(1.03)	57.29	(0.93)
Part-time, using child care	86.42	(1.92)	81.03	(1.75)	56.87	(1.55)
Full-time, no child care	87.36	(1.80)	81.93	(1.73)	57.56	(1.74)
Full-time, using child care	87.45	(1.13)	82.20	(1.08)	58.71	(1.03)

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for Models 1 and 2, and parametrically using 200 repetitions for Model 3.

Table 1.13: Descriptive Statistics of Body Mass Status, by Employment and Child Care Alternatives, and Gender

Employment and Child Care Alternatives	Female	Male	Difference	
Obese (%)				
No work, no child care	11.77	16.49	-4.71	***
	(0.63)	(0.73)	(0.97)	
No work, using child care	20.36	24.14	-3.78	
	(3.13)	(3.57)	(4.72)	
Part-time, no child care	12.28	15.07	-2.79	**
	(0.74)	(0.79)	(1.08)	
Part-time, using child care	14.63	18.16	-3.53	
	(1.52)	(1.69)	(2.27)	
Full-time, no child care	16.13	21.18	-5.05	***
	(0.81)	(0.87)	(1.20)	
Full-time, using child care	16.65	19.90	-3.25	***
	(0.82)	(0.88)	(1.20)	
Overweight (%)				
No work, no child care	26.21	31.65	-5.44	***
	(0.86)	(0.92)	(1.26)	
No work, using child care	34.13	33.79	0.34	
	(3.68)	(3.94)	(5.39)	
Part-time, no child care	25.66	31.54	-5.87	***
	(0.98)	(1.02)	(1.41)	
Part-time, using child care	31.48	33.08	-1.60	
	(2.00)	(2.06)	(2.87)	
Full-time, no child care	32.45	36.83	-4.37	***
	(1.04)	(1.03)	(1.46)	
Full-time, using child care	33.21	35.80	-2.59	*
	(1.03)	(1.05)	(1.48)	
BMI-Percentile				
No work, no child care	58.65	63.21	-4.56	***
	(0.58)	(0.58)	(0.81)	
No work, using child care	64.04	63.87	0.17	
	(2.33)	(2.64)	(3.50)	
Part-time, no child care	59.41	62.87	-3.45	***
	(0.65)	(0.63)	(0.90)	
Part-time, using child care	63.85	64.67	-0.83	
	(1.22)	(1.24)	(1.74)	
Full-time, no child care	63.84	66.53	-2.69	***
	(0.64)	(0.62)	(0.89)	
Full-time, using child care	64.49	65.83	-1.34	
	(0.63)	(0.63)	(0.90)	

Note: *** indicates significance at the 1% level,** 5% level, and * 10% level.

Table 1.14: Descriptive Statistics of Body Mass Status, by Employment and Child Care Alternatives, and Race

Employment and Child Care Alternatives	Race: Non-black Non-Hispanic	Race: Black	Race: Hispanic	Difference between Non-black, Non-Hispanic and: Black		Difference between Non-black, Non-Hispanic and: Hispanic	
Obese (%)							
No work, no child care	11.66	21.00	20.59	-9.34	***	-8.93	***
	(0.52)	(2.28)	(1.23)	(1.92)		(1.18)	
No work, using child care	23.53	20.59	21.30	2.94		2.23	
	(3.65)	(4.94)	(3.96)	(6.23)		(5.41)	
Part-time, no child care	12.02	21.08	22.66	-9.07	***	-10.65	***
	(0.56)	(3.18)	(1.87)	(2.62)		(1.62)	
Part-time, using child care	14.75	27.05	16.07	-12.30	***	-1.32	
	(1.28)	(4.04)	(2.84)	(3.59)		(3.04)	
Full-time, no child care	17.19	19.53	25.34	-2.34		-8.14	***
	(0.68)	(1.83)	(1.69)	(1.88)		(1.66)	
Full-time, using child care	16.46	21.98	23.19	-5.53	***	-6.74	***
	(0.69)	(1.76)	(1.64)	(1.75)		(1.64)	
Overweight (%)							
No work, no child care	25.05	38.24	39.52	-13.19	***	-14.47	***
	(0.71)	(2.73)	(1.48)	(2.55)		(1.54)	
No work, using child care	33.82	36.76	32.41	-2.94		1.42	
	(4.07)	(5.89)	(4.52)	(7.11)		(6.09)	
Part-time, no child care	26.62	38.55	39.17	-11.93	***	-12.54	***
	(0.76)	(3.79)	(2.18)	(3.53)		(2.14)	
Part-time, using child care	30.40	41.80	33.93	-11.40	**	-3.53	
	(1.66)	(4.48)	(3.66)	(4.53)		(3.94)	
Full-time, no child care	32.42	37.15	43.63	-4.74	**	-11.21	***
	(0.84)	(2.23)	(1.92)	(2.33)		(2.02)	
Full-time, using child care	32.30	37.84	41.42	-5.54	***	-9.12	***
	(0.86)	(2.06)	(1.91)	(2.18)		(2.03)	
BMI-Percentile							
No work, no child care	58.67	65.47	67.35	-6.80	***	-8.68	***
	(0.48)	(1.65)	(0.87)	(1.70)		(1.00)	
No work, using child care	62.01	68.65	63.47	-6.64		-1.46	
	(2.83)	(3.39)	(2.84)	(4.67)		(4.07)	
Part-time, no child care	60.12	68.25	65.96	-8.13	***	-5.84	***
	(0.49)	(2.22)	(1.34)	(2.27)		(1.37)	
Part-time, using child care	62.84	69.65	66.85	-6.82	**	-4.02	*
	(1.03)	(2.56)	(2.11)	(2.78)		(2.41)	
Full-time, no child care	63.86	66.31	70.80	-2.45	*	-6.94	***
	(0.52)	(1.37)	(1.08)	(1.44)		(1.23)	
Full-time, using child care	63.19	70.01	69.79	-6.82	***	-6.60	***
	(0.54)	(1.12)	(1.10)	(1.33)		(1.25)	

Note: *** indicates significance at the 1% level,** 5% level, and * 10% level.

Chapter 2

The Impact of Maternal Employment and Alternative Child Care Types on the Health of Young Children

2.1 Introduction

Childhood obesity rates in the United States have increased dramatically over the past three decades. Obesity rates for children between the ages of 6 to 11 for example, increased from 5 to 17 percent between 1976 and 2004 (Centers for Disease Control and Prevention, 2007). Researchers, policymakers, and medical professionals have become increasingly wary of the childhood obesity epidemic as a result of the immediate and long-term implications of being overweight and/or obese in childhood. Therefore, a vast literature examines possible determinants that may have led to the dramatic rise (and acceleration) in the number of obese children.

In this paper, I add to the current literature by examining the impact of two notable factors that also changed during the same time period: the increase in women's labor force participation and in the usage of child care. I extend my analysis in Chapter 1 by examining the effect of alternative *types* of child care, informal and formal before- and/or after-school child care, on children's body mass statuses. Child care can be received in different forms; specifically, child care can be provided in an informal setting, such as with a sibling, relative, or babysitter; or in a formal setting defined as child care that is not provided within a home, such as a child care center and youth activity facilities. Regulations on how formal child care should be provided vary widely by state. Furthermore, there are very few restrictions and/or guidelines on how informal child care should be provided to children. Thus, the quality of child care can vary from individual to individual. Despite being unable to measure the quality of child care, I am able to differentiate between informal and formal child care settings in this paper.

There are several mechanisms through which the effect of informal and formal child care settings on the body mass status of young children may differ. For instance, children in informal child care settings who have relatives, such as grandparents, taking care of them may be less likely to engage in rigorous activities if grandparents are unable to participate in rigorous activities with the child. However, babysitters may be more likely to engage in rigorous play and pay greater attention to what the children are eating, because they only have to pay attention to one child (compared to large numbers of children in child care facilities).

In a similar light, the impact of child care received in formal child care facilities is not clearly understood. Child care facilities that stick to regimented eating and activity schedules may be more likely to feed healthy snacks and to have children participating in rigorous play with their peers; however, the large number of children in a given facility may make it difficult for care givers to provide individualized attention that informal child care providers may be able to give. Without further empirical investigation it is difficult to ascertain whether there truly are differences in the effect of child care by the type of care received.

The current literature on children's obesity focuses infrequently on the impact of employment and child care. Furthermore, relatively little attention has been given to the impact of alternative child care types on children's health. Therefore, in this paper I examine the impact of mothers' employment and alternative child care decisions on the body mass status of elementary school-age children. This work also suggests an area of further exploration with regard to cognitive outcomes of children. Despite a large number of studies on cognitive outcomes, one major shortcoming of the available literature is that the effects of employment and child care are examined separately (despite a strong relationship between mothers employment and child care usage).

I use data from the Early Childhood Longitudinal Study, Class of 1998-1999 (ECLS-K). In estimation, I control for possible unobserved heterogeneity that may bias the effect of employment and child care on the health and cognitive outcomes of children. I jointly estimate the employment and child care decision equation with the health and cognitive outcome equations allowing for the error components to be correlated both contemporaneously and over time. I also examine the effects of informal and formal child care separately and find that informal child care (for full-time workers) is associated with a significant increase in children's risk of being overweight and on BMI-percentile. Furthermore, I find that full-time employment reduces the risk that a child is overweight or obese.

2.2 Background

2.2.1 Literature Review

Due to the potential detriments of childhood obesity to children's physical and emotional health, and the long-run impact of poor body mass health in childhood on future health, researchers have been determined to find the potential source(s) of the childhood obesity problem. As such, a large body of literature has analyzed the impact of individual, environmental, and social factors on the body mass status of children. Researchers have analyzed for instance, state-level policies on time devoted to physical education in schools, the number of vending machines available within a school, and parks and recreational areas in close proximity to children's residences and their effects on children's body mass statuses. Despite a large number of potential factors that may have contributed to the widespread obesity problem, policymakers have yet to reach a consensus on how best to reduce childhood obesity rates.

One of the topics that researchers have been particularly interested in is the effect of maternal employment on children's obesity risk. Children, especially those that are young, are highly influenced by the decisions of their parents. Thus, researchers have evaluated the potential risk of working mothers on the risk of obesity and overweight. Currently, the evidence is inconclusive. To summarize, mothers' employment potentially increases children's obesity risk, but many of the papers with such a conclusion have failed to account for potential unobservable variables correlated with employment decisions and children's obesity risk that may bias the result. Papers that have controlled for potentially unobservable variables (Anderson et al, 2003) tend to find that the detrimental effects disappear after controlling for the unobservables. A more detailed discussion of these papers is available in Chapter 1.

Papers examining the impact of child care on children's obesity risk, are currently (that I am aware of) rare. Frisvold (2006) studies the impact of Head Start, a national program that encourages profit and non-profit institutions to promote school-readiness in economically disadvantaged children and families through grants, on children's obesity risk. Nutritional guidelines to organizations that accept their grants are set by the Office of Head Start. As such, Frisvold finds that those who participate in the program see a significant reduction in the probability of overweight and obesity in later childhood. This analysis however, is restricted in that it is restricted to a particular child care setting with highly specific guidelines.

Interestingly, a large number of papers have looked at the effect of employment and child care on children's cognitive ability. The results in these analyses have also been quite inconclusive. For example, Baydner and Brooks-Gunn (1991) find that maternal employment in the first year of a child's life negatively affects cognitive outcomes on a group of four year old children. On the other hand, Parcel and Menaghan (1994) find that the negative effects found by Baydner and Brooks-Gunn are unfounded using an alternative sample of children. The impact of child care on cognitive outcomes differs greatly by empirical approach, age of the children, and the type of child care received.

2.2.2 Overview

This paper examines the impact of maternal employment and informal and formal child care on the physical and congitive well-being of elementary school-age children and contributes to the current literature as follows. First, I address the current void in the literature on the differences in informal and formal child care on children's body mass status. In addition, I examine the impact of employment and informal and formal child care on children's cognitive well-being. This analysis differs from the current literature in that I study the effects of before- and/or after-school care, rather than all day child care. Second, I model the employment and child care decisions as joint, rather than separate, decisions. Lastly, I address possible endogeneity issues that can result in biased effects of the mothers' employment and child care choices on children's well-being using a joint semi-parametric estimation technique. This estimation method controls for individual time-invariant and time-varying heterogeneity that may be correlated with the joint employment and child care decision, and children's well-being.

2.3 Empirical Model

2.3.1 Empirical Specification

I begin by specifying an equation for the joint demand for maternal employment and child care, and an equation for the child's well-being. In the empirical model, I collapse the employment and child care decisions into eight mutually exclusive combinations:[1]

$$d = \begin{cases} 0 & \text{if Not working and not using child care} \\ 1 & \text{if Not working and using child care (formal or informal)} \\ 2 & \text{if Working part-time and not using child care} \\ 3 & \text{if Working part-time and using informal child care} \\ 4 & \text{if Working part-time and using formal child care} \\ 5 & \text{if Working full-time and not using child care} \\ 6 & \text{if Working full-time and using informal child care} \\ 7 & \text{if Working full-time and using formal child care} \end{cases} \tag{2.1}$$

where $D_t = d$ represents the joint employment and child care decision. Individuals not working are defined as those working between zero and eight hours per week, part-time if working between eight and thirty five hours per week, and full-time if working more than 35 hours per week. Individuals are defined as using informal child care (i.e., child care provided by a relative, siblings, or babysitter) and formal child care (i.e., child care in a facility that is not in one's home) if the weekly number of hours exceeds 5.

In estimation, I capture two sources of unobserved heterogeneity, time-invariant permanent

[1] d=2 includes both mothers who did not work and used either informal or formal child care (instead of having those who used informal and formal child care as separate categories). This was due to having very few people that used child care if they did not work.

and time-varying heterogeneity. Examples of time-invariant permanent heterogeneity include factors that are possibly correlated with a mother's employment and child care decision, that may also be correlated with the child's health outcome that *do not change over time.* These include factors such as motivation or a child's inherent health. Time-varying heterogeneity is determinants that may change over time, including factors such as a mother or child's emotional and psychological well-being. The error term in the joint employment and child care decision, ϵ_{1t}^{d}, and the error term in the body mass status outcome equation, ϵ_{2t}, are decomposed into two sources of unobserved (to the econometrician) heterogeneity and expressed as

$$\begin{aligned} \epsilon_{1t}^{d} &= \mu_1^d + \nu_{1t}^d + e_{1t}^d \quad \forall d = 0, ..., 7 \\ \epsilon_{2t} &= \mu_2 + \nu_{2t} + e_{2t}, \end{aligned}$$

where μ_1^d and μ_2 capture the time-invariant and ν_{1t}^d and ν_{2t} capture the time-varying sources of unobserved heterogeneity, and e_{1t}^d and e_{2t} are the remaining error components that are identically and independently distributed.

The employment and child care decision, assuming that e_{1t} is Type-I Extreme Value distributed, conditional on the unobserved heterogeneity components (μ and ν), can be written in log odds as

$$\ln\left[\frac{\Pr(D_t = d|\mu_1, \nu_{1t})}{\Pr(D_t = 0|\mu_1, \nu_{1t})}\right] = \gamma_{0d} + \gamma_{1d}B_t + \gamma_{2d}X_t + \gamma_{3d}P_t + \gamma_{4d}Z_t + \mu_1^d + \nu_{1t}^d \quad d = 1, ..., 7, \quad (2.2)$$

where the decisions are functions of body mass status entering the period (B_t), exogenous variables (X_t and P_t), and exclusion restrictions (Z_t).[2]

Assuming (for ease) that the health outcome is a dichotomous specification, the production function conditional on the unobserved heterogeneity components (μ and ν_t) can be expressed as

$$\ln\left[\frac{\Pr(B_{t+1} = 1|\mu_2, \nu_{2t})}{\Pr(B_{t+1} = 0|\mu_2, \nu_{2t})}\right] = \beta_0 + \beta_1 B_t + \beta_2 D_t + \beta_3 B_t D_t + \beta_4 X_t + \beta_5 P_t + \mu_2 + \nu_{2t}. \quad (2.3)$$

[2]Further detail on the exogenous variables are available in Tables 1.1 and 1.2

In estimation, I consider three different specifications of the dependent variable: (1) a child's Body Mass Index (BMI) percentile-for-age-and-sex, and (2) two dichotomous health outcomes where I define a child to be overweight or obese if his BMI-percentile-for-age-and-sex is above a given threshold. In addition to body mass status, I also consider two other continuous measures of a child's well-being, a child's reading and math achievement scores.[3]

The estimation technique employed in this analysis is a joint estimation semi-parametric method: the discrete factor estimation technique (DFM). The primary reason for using this estimation technique is to control for the possible correlation of the error terms across equations that results in endogeneity bias. Unlike many studies that use a maximum likelihood estimation method, this approach does not impose any distributional assumptions, such as joint normality, on the error terms. Instead the unobserved heterogeneity components are approximated as discrete step-wise distributions (see Heckman and Singer, 1984; Mroz and Guilkey, 1992; Mroz, 1999).

The unconditional likelihood function for individual i

$$\begin{aligned} \mathrm{L}_i(\Theta, \psi, \pi) \quad = \quad & \sum_{k=1}^{K} \pi_k \Bigg\{ \Pr(B_1 = 1|\mu_{2k})^{B_{i1}} [1 - \Pr(B_1 = 1|\mu_{2k})]^{1-B_{i1}} \\ & \times \prod_{t=1}^{T} \sum_{\ell=1}^{L} \psi_\ell \Bigg[\prod_{d=0}^{7} \Pr(D_t = d|\mu_{1k}^{d}, \nu_{1t\ell}^{d}) \mathbf{1}[D_{it} = d] \\ & \Pr(B_{t+1} = 1|\mu_{2k}, \nu_{2t\ell})^{B_{it+1}} [1 - \Pr(B_{t+1} = 1|\mu_{2k}, \nu_{2t\ell})]^{1-B_{it+1}} \Bigg] \Bigg\} \end{aligned} \quad (2.4)$$

where Θ is the vector of variables in the model that are to be estimated.

The distribution of the time-invariant heterogeneity (μ) is given by

$$\pi_k = \Pr(\mu_1^0 = \mu_{1k}^0, ..., \mu_1^7 = \mu_{1k}^7, \mu_2 = \mu_{2k}) \qquad k = 1, ..., K \quad (2.5)$$

where K is the number of time-invariant mass points. The distribution of the time-varying

[3]The following empirical model assumes for now that the outcome is body mass status. However, a detailed description of the model is available in Appendix B.1.

heterogeneity (ν_t) is given by

$$\psi_\ell = \Pr(\nu_{1t}^0 = \nu_{1t\ell}^0, ..., \nu_{1t}^7 = \nu_{1t\ell}^7, \nu_{2t} = \nu_{2t\ell}) \qquad \ell = 1, ..., L, \forall t \tag{2.6}$$

where L is the number of time-varying mass points. In summary, the unobserved heterogeneity components are modeled as discrete random effects with several points of support that is empirically evaluated.

2.4 Data

This analysis uses longitudinal data from the Early Childhood Longitudinal Study, Kindergarten Class of 1998-1999 (ECLS-K). The ECLS-K is a nationally representative study of 21,409 children who were in kindergarten in 1998. The survey has followed these children from kindergarten until the eight grade and includes detailed information about the child's emotional, cognitive, and physiological well-being, and his/her home and school environments. A more in depth description of this data can be found in the data section in Chapter 1.

2.4.1 Description of Key Variables

Body Mass Status Outcome Measures

Data from the parent/guardian interview are used to construct body mass status measures, specifically a child's body mass index (BMI), a ratio of weight in kilograms to height in meters squared. For adults (those over the age of 20) individuals are classified as being overweight if their BMI exceeds 25, obese if it exceeds 30, and morbidly obese if it exceeds 35. However, children's BMIs are used in a slightly different manner to account for children's growth and development. Using growth charts developed by the Centers for Disease Control and Prevention (CDC), an individual child's BMIs is compared to other children of the same gender and age. The growth charts then allow these children to then be assigned a BMI-percentile for a given age and gender cohort.[4] I then use classifications determined by the CDC where children with a

[4] A detailed description of BMI-percentiles is available in Appendix A.4.

BMI-percentile-for-sex-and-age (referred from this point on as BMI-percentile) greater than the 85th percentile are overweight and those exceeding the 95th percentile are obese. As previously stated, three specifications of body mass status are then considered in estimation: risk of being obese, risk of being overweight, and BMI-percentile.

Cognitive Outcome Measures

In this chapter, I also evaluate the effects of employment and child care decisions on two cognitive outcomes measures: reading and math scores. The ECLS-K collects direct cognitive assessments in three major subjects: reading, which evaluates a child's comprehension of language and literacy; mathematics, which measures understanding of math specific to each given grade; and general knowledge, which assesses the understanding of topics in science and social studies. These tests were developed using national- and state-level standards.

In this anlaysis, I use reading and mathematics scores as measures of a child's cognitive outcome. The survey includes two different types of scores, a number-of-correct answers score, and a standardized score, where the values are along a 0-100 scale. The reading score assesses factors such as familiarity with print, letters, and multisyllabic work, reading comprehension, and vocabulary knowledge. The mathematics component measures problem solving skills and conceptual knowledge.

Employment and Child care Measures

Mothers' employment hours and the hours spent in child care are collected in the survey and I divide the measure into three categories: less than or equal to 8 hours per week (referred to as *no-work*), between 8 and 35 hours per week (referred to as *part-time*, and more than 35 hours per week (referred to as *full-time*). These three categories will allow for differences in the effect on children's outcome by work intensities to be captured.

The number of hours spent in child care is also collected in the survey. Since my analysis examines children who are in elementary school, the majority of regularly received child care (defined as receiving care more than once per week) is before- or after-school care. Furthermore, the data distinguishes between types of care received: informal with a relative (e.g., relatives or siblings), informal with a non-relative (e.g., babysitter), and formal child care (e.g., child care centers such as YMCAs). Using this information, I define a child to be using informal child care if the total number of hours spent in informal care with/without a relative exceeds 5 hours per week and I define a child to be using formal child care if the total number of hours spent in formal child care exceeds 5 hors per week.

In Table 2.1, I present percentages of children in my sample in alternative employment and child care categories. I find that around 71% of children do not use any type of child care (regardless of mother's employment status). 18.5% of children use informal child care and 10.3% use formal child care. In addition, informal child care is used more often than formal child care regardless of the mother's employment status.

2.4.2 Description of Explanatory Variables

In the analysis, I control for child characteristics (X_t), including age, sex, and race; parental characteristics (also included in the vector X_t), including the mother and father's education and age, and area-level characteristics (P_t) that capture the price and availability of food and activity in a child's residence area, including the number of supermarkets, fitness centers, and convenience stores, and the price of full-service and fast food restaurants. Details of the explanatory variables used in this analysis is available in the data section in Chapter 1.

2.4.3 Identification

Similar to the analyses in Chapter 1, identifying variables for the employment and child care decision equation include: county-level poverty and unemployment rates, county-level median income, high school and college completion rates for a given state, benefit levels from the Temporary Assistance for Needy Families (TANF) program for a family of four, and mandatory job search requirements for TANF recipients to capture wages (W_t); and county-level mean wage of child care workers, total number of child care facilities (group home and regulated child care) per 1,000 people in a state, and state-level licensing requirements to capture child care prices (P_t^c). Mothers may be less inclined to leave a full-time employment position under poor market conditions (captured by poverty and unemployment rates, and median income).

Further, stricter welfare rules may make mothers more likely to work. Lastly, the number of child care facilities, stringency of licensing requirements for child care centers, and the mean wage of child care workers may reflect the price of child care and the likelihood of child care usage.

Initial body weight status is identified by county- and state-level variables, such as price of food, availability of restaurants and fitness centers, and child care workers' wages, from the corresponding year, as well as the child's birth weight (in kilograms). In addition to the county- and state-level characteristics, all lagged exogenous variables and the nonlinearity of the model provide additional identification in this system of dynamic equations (Yang et al., 2009).

2.5 Results

I begin in Sections 2.5.1 and 2.5.2 by showing results from the body mass status outcome. In Section 2.5.1, I discuss the marginal effects (i.e., short run impact) of alternative employment and child care choices on three different body mass status outcomes: risk of being obese, risk of being overweight, and BMI-percentile. In Section 2.5.2, I present and discuss long run simulation results that quantify the long run impact of employment and child care decisions on future health. In Sections 2.5.3 and 2.5.4, I discuss marginal effects and long run results respectively, that evaluate the impact of maternal employment and child care on children's cognitive outcomes. A discussion on the empirical model used to analyze cognitive outcomes is available in Appendix B.1.

2.5.1 Estimation Results for Body Mass Status Outcomes

In Table 2.2, I present simple summary statistics of the three different body mass status outcomes for alternative employment and child care categories. In the first column, I present the percentage of individuals that are obese, in column 2 the percentage of individuals that are overweight, and in column 3 BMI-percentiles. The table shows that compared to not working and not using child care, working full-time and not using child care increases the risk that a child is obese by around 4 percentage points; increases the risk of being overweight by around

5 percentage points; and BMI by around 4 percentile points. For full-time workers, using child care (informal or formal) reduces the risk of being obese or overweight. This reduction is however, greater for those participating in formal, rather than informal, child care. At first glance, these results suggest that the impact of employment may be detrimental to the health of a child however, the results do not control for possible unobservables that may by correlated with the employment and child care choices and child health.

In Tables 2.3 to 2.5, short run effects of alternative employment and child care choices on the risk of being obese, risk of being overweight, and BMI-percentile respectively, are shown. Model 1a estimates body mass status as a function of the eight alternative employment and child care choices (where no work, no child care is the omitted category) only. Model 1b then adds controls for exogenous mother, father, child, and community characteristics (X_t, P_t), and lastly Model 1c adds lagged health (B_t) into the specification. All three of these models do not control for possible unobservable characteristics that may affect employment and child care choices, and child health. Standard errors (in parentheses) are bootstrapped non-parametrically with 200 draws.

Results from Model 1a, 1b, and 1c show that full-time employment has a detrimental impact (i.e., increases) on children's risk of being obese and of being overweight. For instance, in Model 1a, I find that full-time employment with child care significantly increases obesity risk (Table 2.3) by 4.6 percentage points, overweight risk (Table 2.4) by 5.8 percentage points, and BMI-percentile (Table 2.5) by around 4 percentile points. Similarly, full-time employment with informal child care significantly increases obesity risk by 5.5 percentage points, overweight risk by 8 percentage points, and BMI-percentile by 5.5 percentile points. Surprisingly, the effect of full-time employment with formal child care is insignificant on the risks of being overweight or obese, but significant and positive for BMI-percentile; however, this effect is around 3 percentile points lower than full-time employment with informal care. The addition of covariates (Model 1b and 1c) reduces the detrimental impact of employment and child care on child health. Full-time employment with informal care continues to increases obesity and overweight risk significantly. However, full-time employment with formal care significantly increases obesity risk, but not the risk that a child is overweight.

The reduction in the impact of full-time employment on children's health suggests that failure to control for observable (and unobservable) characteristics can overbias the employment and child care effects. In addition, these results, which do not control for possible unobservable variables influencing employment and child care decisions and child health, suggest the possibility that the negative impact of child care on children's health may be driven by informal child care rather than formal child care.

Models 2a, 2b, and 2c have the same specifications as those in Models 1a, 1b, and 1c except that these models control for permanent individual heterogeneity. I find that the detrimental effect of full-time employment on children's obesity and overweight risk, as seen in Models 1a-1c, are not observed in these results. The difference in the results from Model 1 suggests that there are permanent unobservable characteristics influencing the employment and child care decision and child health.

Model 3, the preferred model, controls for both permanent and time-varying unobservable characteristics that my influence the employment and child care decision, and child health. Results in Table 2.3 which evaluate the impact of employment and child care on children's obesity risk shows that full-time employment with no child care reduces the risk by around 2.5 percentage points compared to not working and not using child care. Furthermore, full-time employment with informal child care also decreases the risk by around 1.6 percentage points whereas the effect of full-time employment with formal child care is insignificant.

The effect on the risk of being overweight, shown in Table 2.4, shows that the impact of full-time employment with no child care reduces the risk by around 2.3 percentage points. The risk of full-time employment with informal child care is insignificant whereas the impact of full-time employment with formal care reduces the risk by 5.9 percentage points. These results suggest that there indeed are unobserved time-varying characteristics influencing the employment and child care decision, and child health and failure to control for these unobservables can lead to an upward bias (i.e., less negative) effect of mothers' choices on their health of children.

Lastly, in Table 2.5 I present results from BMI-percentile as the body mass status outcome. I find that full-time employment with no child care significantly reduces BMI-percentile by around 0.4 percentile points, compared to not working and not having child care. Full-time employment with informal child care however, has a positive but insignificant effect. Full-time employment with informal child care on the other hand, greatly reduces BMI-percentile by around 2 percentile points.

2.5.2 Simulation Results for Body Mass Status Outcomes

The results presented in Tables 2.3 to 2.5 are short run effects of the employment and child care choices on children's health. Since the model is dynamic, it is possible to examine the long run impact of the employment and child care alternatives. Specifically, I evaluate the effect of a particular employment and child care alternative over the three sample periods (when the children were in the first, third, and fifth grades) to capture the long run impact of a particular choice. I begin the simulation by assigning all individuals to a particular employment and child care category in the first, third, and fifth grades. I use the child's observed body mass status (rather than estimating the body mass status using the initial condition equation) in kindergarten to predict the child's body mass status at the end of first grade using the estimated coefficients. Then, the predicted body mass status is used to update lagged body mass status in the next period and to predict body mass status in the third grade. This is repeated to predict the long run effect of an employment and child care alternative on body mass health in the last period.

In Table 2.6, I present predicted risks of being obese and overweight, and predicted BMI-percentile-for-age-and-sex in the fifth grade under the eight different employment and child care care alternatives. I simulate long run results for three different models: Model 1c, that does not control for unobservable heterogeneity; Model 2c, that controls for permanent heterogeneity; and Model 3, that controls for permanent and time-varying unobservable heterogeneity. The results from Model 1c would suggest that compared to not working and not using child care, working full-time and using child care increases the risk that a child is obese. However, Models 2c and 3, which control for permanent heterogeneity and both permanent and time-varying heterogeneity respectively, indicate that full-time employment reduces obesity risk. For the risk of being overweight, Model 1c would indicate that the effect of full-time employment with no child care or with informal child care would increase the risk of being overweight. After controlling for permanent and time-varying heterogeneity (Model 3), the results show that full-time employment with no child care or with formal child care reduces the probability of being overweight; however, the effect of full-time employment with informal child care increases the risk that a child is overweight.

In Tables 2.7 to 2.9, I present differences in the effect of employment and child care alternatives. In the upper column, I compare the alternative choices to no work and no child care; in the middle column to full-time work and no child care; and the lowest column to full-time work and informal child care. In Table 2.7, I find that compared to not working and not using child care, full-time employment and not using child care decreases the risk that a child is obese in the fifth grade by around 7 percentage points. Full-time employment with informal child care decreases obesity risk by 4.8 percentage points.

In Table 2.8, where differences for the risk of being overweight are presented, I find that full-time employment with no child care reduces the risk that a child is overweight by around 7 percentage points (compared to not working and not using child care). However, full-time employment with informal care increases the risk of being overweight by around 1.8 percentage points. Full-time employment with formal child care however, reduces the risk that a child is overweight by 16 percentage points. Thus, for full-time workers using informal child care has a large and significant effect of around a 9 percentage point increase in the risk of being overweight, whereas formal child care reduces the risk that a child is overweight by around 9 percentage points.

Lastly in Table 2.9, where differences in BMI-percentile are shown I find that full-time employment with no child care has a negative, yet insignificant effect on BMI-percentile when compared to not working and not using child care. Full-time employment with informal child care has a positive impact on BMI-percentile. For full-time workers, going from no child care to informal child care increases BMI-percentile by around 1.5 percentile points. However, formal child care decreases BMI-percentile by around 3 percentile points.

2.5.3 Estimation Results for Cognitive Outcomes

In Table 2.10, I present simple summary statistics of the two cognitive outcome measures, reading and math scores, by employment and child care alternatives. I find that compared to not working and not using child care, working full-time and not using child care reduces reading and math scores by about 1 percentile point. Full-time employment with formal child care seems to have very little effect on cognitive outcomes, whereas full-time work with informal child care reduces both reading and math scores by around 2 percentile points. These results suggest that full-time employment and using informal child care reduces children's cognitive outcome however, these simple summary statistics do not control for potential observable and unobservable characteristics that influence the employment and child care decision and children's cognitive well-being.

In Tables 2.11 and 2.12, short run effects of alternative employment and child care choices on children's reading and math scores are shown. Model 1a estimates the impact of the eight alternative employment and child care choices on cognitive well-being, not controlling for observables. Model 1b adds observable child and parental characteristics, and Model 1c then adds lagged reading (mathematics) scores into the model. All three models do not control for possible unobservable characteristics that may affect the employment and child care decision, and children's cognitive outcomes.

Models 2a, 2b, and 2c have the same specification as Models 1a-1c, except that it controls for potential permanent heterogeneity. Comparing Model 1c to 1a, I find that controlling for permanent heterogeneity increases (i.e., makes less negative) the effect of the employment and child care characteristics on children's reading and math scores. This finding suggests that the permanent heterogeneity may have confounded the effect of employment and child care on children's cognitive well-being.

In Model 3, the preferred model, I find that the effect of employment and child care characteristics are not significant in most cases. The preferred model jointly estimates the employment and child care decision equation with the reading and math score equations. These estimates produce point estimates where the standard errors are quite large (compared to the other models), despite the identifying instruments passing tests of overidentification and joint significance.

These results suggest that the detrimental impact of employment and child care observed in Models 1a-1c may have been confounded with time-invariant and time-varying unobservables.

2.5.4 Simulation Results for Cognitive Outcomes

The results presented in Tables 2.13 to 2.15 are long run simulations evaluating the impact of the eight alternative employment and child care choices. In Table 2.13, the predicted reading and math scores under the eight employment and child care alternatives are presented. I compare long run predictions from 3 models: Model 1c, where I do not control for any potential unobservable variables; Model 2c, where I control for potential permanent heterogeneity; and Model 3, where I control for both permanent and time-varying heterogeneity. At first glance, the predicted scores show very little differences by employment and child care choices.

In Tables 2.14 and 2.15, I present differences in math and reading scores to examine whether there are significant differences in scores by employment and child care alternatives. Results that do not control for unobservable characteristics (Model 1c) would suggest that there is a detrimental effect of full-time employment (regardless of child care) on children's reading and math scores. This finding is similar to many previous studies and is consistent with the story that mothers who work may have less time to devote to children, thereby reducing their tests scores. However, results from Model 2c and 3 suggest that there is very little difference in math scores by employment and child care alternatives. On the other hand, reading scores seem to increase by around 0.04 points for full-time workers with informal child care compared to full-time workers with no child care.

2.6 Discussion and Summary

With the rapid rise in childhood obesity rates, researchers have become greatly interested in understanding what factors may have contributed to the obesity epidemic. This analysis examines two potential contributing factors, mother's employment and informal and formal child care usage, on children's body mass status. In addition, I add to a large and inconclusive literature on the impact of employment and child care on children's cognitive outcomes. In summary, there are three main findings from this analysis. First, full-time employment with no child care (compared to no work and no child care) decreases the risks of being obese and overweight. Second, informal child care for full-time workers increases the risk that a child is overweight and also increases BMI-percentile at the mean. And lastly, results from my preferred model indicate that there is very little impact of employment and child care on children's cognitive well-being.

There are a few mechanisms that may explain why maternal employment can reduce the risk of children being obese or overweight. Employed mothers for example, may have more income to devote to the well-being of their children. If the health benefits of maternal employment are due to an income effect, then the reduction in the risk of obesity and being overweight should disappear after controlling for mother's income. Although, I am unable to control for the mother's income, due to data limitations in the ECLS-K, when I controlled for total household income (the only income variable in the data), I found that the beneficial effect of maternal employment was still present on a slightly smaller magnitude. Thus, these findings suggest that mothers who work may not necessarily spend less time caring for their children. In addition, because this analysis focuses on children who are in elementary school, mothers who work only while their children are at school may be able to spend as much time with their children as mothers who are not employed.

For full-time workers, informal child care, unlike formal child care, has a significantly detrimental effect on children's risk of being overweight and on BMI-percentile. These findings suggest that the detrimental effect of child care observed in Chapter 1 may have been driven by informal child care. Several reasons may explain this result. First, informal child care providers may be less qualified to take care of children than providers in formal child care centers. Furthermore, informal child care providers may be unable to provide regimented care in the same manner as formal child care centers, resulting in higher consumption of poor quality foods and decreased participation in rigorous activities.

Lastly, I find that there seems to be very little impact of employment and child care on children's cognitive development. This may be explained by the age of the children used in the analysis. Since all of the children in my sample are in elementary school, full-time employment and before- and/or after-school care may not significantly influence cognitive scores.

This analysis contributes to the current literature in the following ways. First, I extend the literature by examining the joint impact of employment and informal and formal child care on children's body mass and cognitive well-beings. Second, I analyze a dynamic model that allows past decisions to affect future decisions. As a result, I can simulate long run effects of the employment and child care decisions. Lastly, this is one of the first studies (that I am aware of) to model not only permanent unobservable heterogeneity, but also time-varying heterogeneity that may affect the employment and child care care decision and children's well-beings.

This analysis lays the foundation for future work on the effects of employment and child care on children's health and provides insight into the potential detrimental impact of informal child care on children's health. Despite extending the current literature by analyzing informal and formal child care settings separately, I am unable to capture the *quality* of child care settings that may provide more information on how to better monitor or regulate child care. Furthermore, it may be interesting (if the data were available) to examine the avenues through which informal child care affect children's health to answer questions such as: is the increase in obesity and overweight risk through activity or dietary behaviors? This analysis highlights the importance of analyzing the employment and child care choices as joint decisions and a deeper understanding of the current child care system may be necessary to promptly address the current childhood obesity epidemic.

Table 2.1: Descriptive Statistics of Employment and Child Care Alternatives

	Employment alternatives			
	Not working	Part-time	Full-time	Overall
Child Care Alternatives				
Not using child care	26.0	22.7	22.4	71.1
Using Informal child care	1.0	3.7	13.8	18.5
Using Formal child care	0.6	1.9	7.9	10.3
Overall	27.6	28.2	44.1	100.0

Note: These are percentages of the sample in alternative employment and child care categories.

Table 2.2: Descriptive Statistics of Body Mass Status by Employment and Child Care (informal and formal) Alternatives

Employment and child care Alternatives	Obese (%)	Overweight (%)	BMI
No work, no child care	14.3	29.0	61.0
No work, using (formal/informal) child care	22.4	34.4	63.9
Part-time, no child care	13.5	28.5	61.0
Part-time, informal child care	19.4	36.1	66.1
Part-time, formal child care	10.6	24.4	60.8
Full-time, no child care	18.7	34.7	65.2
Full-time, informal child care	16.0	30.3	62.8
Full-time, formal child care	14.8	29.3	61.2

Table 2.3: Marginal Effect of Maternal Employment and Child Care (informal and formal) Alternatives on the Risk of Being Obese

	Exogenous			Individual Fixed Effect			Joint
Employment and child care alternatives	Model 1a	Model 1b	Model 1c	Model 2a	Model 2b	Model 2c	Model 3
No work, no child care	Omitted Category						
No work, use child care	0.087 ***	0.045 **	0.006	0.004	0.004	0.004	-0.004
(informal or formal)	(0.027)	(0.023)	(0.012)	(0.019)	(0.017)	(0.020)	(0.013)
Part-time, no child care	-0.009	-0.003	-0.001	0.002	-0.010	-0.010	-0.016 *
	(0.008)	(0.008)	(0.005)	(0.008)	(0.007)	(0.008)	(0.008)
Part-time, informal child care	0.055 ***	0.050 ***	0.019 *	-0.003	-0.002	-0.003	0.001
	(0.017)	(0.018)	(0.011)	(0.015)	(0.015)	(0.015)	(0.012)
Part-time, formal child care	-0.042 **	-0.037 **	-0.021	-0.006	0.005 *	0.001 *	-0.043 *
	(0.020)	(0.019)	(0.017)	(0.017)	(0.017)	(0.019)	(0.026)
Full-time, no child care	0.046 ***	0.030 ***	0.002	0.001	-0.016	-0.016	-0.025 ***
	(0.008)	(0.008)	(0.005)	(0.009)	(0.010)	(0.009)	(0.008)
Full-time, informal child care	0.055 ***	0.034 ***	0.009	-0.009	-0.011	-0.011	-0.016 *
	(0.009)	(0.011)	(0.007)	(0.011)	(0.011)	(0.011)	(0.009)
Full-time, formal child care	0.019	0.019 *	0.013 *	-0.012	-0.008	-0.008	-0.014
	(0.012)	(0.012)	(0.008)	(0.014)	(0.013)	(0.013)	(0.012)
Controls for:							
Exogenous characteristics	No	Yes	Yes	No	Yes	Yes	Yes
Lagged health	No	No	Yes	No	No	Yes	Yes

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for Models 1 and 2, and parametrically using 200 repetitions for Model 3. Model 3 is estimated using 7 permanent and 2 time-varying heterogeneity mass points.
*** indicates significance at 1%, ** 5%, and * 10%. Coefficient from estimation are available in Appendix B.1.

Table 2.4: Marginal Effect of Maternal Employment and Child Care (informal and formal) Alternatives on the Risk of Being Overweight

	Exogenous			Individual Fixed Effect			Joint
Employment and child care alternatives	Model 1a	Model 1b	Model 1c	Model 2a	Model 2b	Model 2c	Model 3
No work, no child care				Omitted Category			
No work, use child care	0.056 **	0.013	-0.017	-0.007	-0.008	-0.010	-0.029 *
(informal or formal care)	(0.027)	(0.028)	(0.015)	(0.023)	(0.026)	(0.025)	(0.018)
Part-time, no child care	-0.005	0.002	-0.002	0.000	-0.020 **	-0.020 *	-0.005
	(0.010)	(0.011)	(0.007)	(0.010)	(0.010)	(0.011)	(0.012)
Part-time, informal child care	0.074 ***	0.067 ***	0.014	-0.002	-0.004	-0.003	-0.012
	(0.020)	(0.021)	(0.013)	(0.019)	(0.019)	(0.020)	(0.015)
Part-time, formal child care	-0.048 *	-0.040 *	-0.030	-0.025	-0.008	-0.007	0.020
	(0.026)	(0.024)	(0.022)	(0.023)	(0.025)	(0.027)	(0.045)
Full-time, no child care	0.058 ***	0.037 ***	0.005	0.010	-0.019	-0.018 *	-0.023 *
	(0.010)	(0.010)	(0.007)	(0.012)	(0.013)	(0.011)	(0.014)
Full-time, informal child care	0.080 ***	0.056 ***	0.023 ***	0.005	0.001	-0.001	0.007
	(0.012)	(0.011)	(0.009)	(0.015)	(0.014)	(0.014)	(0.014)
Full-time, formal child care	0.013	0.013	0.001	-0.032 **	-0.029 *	-0.029 *	-0.059 ***
	(0.014)	(0.015)	(0.010)	(0.015)	(0.016)	(0.016)	(0.017)
Controls for:							
Exogenous characteristics	No	Yes	Yes	No	Yes	Yes	Yes
Lagged health	No	No	Yes	No	No	Yes	Yes

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for Models 1 and 2, and parametrically using 200 repetitions for Model 3. Model 3 is estimated using 9 permanent and 2 time-varying heterogeneity mass points.
*** indicates significance at 1%, ** 5%, and * 10%. Coefficient from estimation are available in Appendix B.1.

Table 2.5: Marginal Effect of Maternal Employment and Child Care (informal and formal) Alternatives on BMI-Percentile

	Exogenous			Individual Fixed Effect			Joint
Employment and child care alternatives	Model 1a	Model 1b	Model 1c	Model 2a	Model 2b	Model 2c	Model 3
No work, no child care	Omitted Category						
No work, use child care	2.905 *	0.211	-0.355	-0.188	-0.160	-0.133	-1.644 ***
(informal or formal)	(1.838)	(2.001)	(0.954)	(1.240)	(1.318)	(1.153)	(0.818)
Part-time, no child care	-0.010	0.648	0.274	0.034	-0.805 *	-0.795	-1.019 **
	(0.617)	(0.639)	(0.345)	(0.511)	(0.495)	(0.501)	(0.386)
Part-time, informal child care	5.055 ***	4.514 ***	1.311	-0.569	-0.650	-0.720	37.076 ***
	(1.052)	(1.190)	(0.757)	(0.904)	(0.760)	(0.833)	(0.911)
Part-time, formal child care	-0.182	0.454	-1.522	-1.854 *	-1.166	-1.176	2.963
	(1.521)	(1.582)	(0.899)	(1.221)	(1.311)	(1.271)	(0.980)
Full-time, no child care	4.189 ***	3.192 ***	0.651	0.508	-0.678	-0.690	-0.413 *
	(0.610)	(0.590)	(0.353)	(0.552)	(0.558)	(0.617)	(0.458)
Full-time, informal child care	5.468 ***	4.082 ***	1.289	0.653	0.454	0.487	0.445
	(0.711)	(0.803)	(0.462)	(0.692)	(0.716)	(0.707)	(0.557)
Full-time, formal child care	1.797 **	1.952 **	0.028	-1.487 *	-1.366 *	-1.370	-2.014 ***
	(0.774)	(0.935)	(0.504)	(0.821)	(0.781)	(0.879)	(0.634)
Controls for:							
Exogenous characteristics	No	Yes	Yes	No	Yes	Yes	Yes
Lagged health	No	No	Yes	No	No	Yes	Yes

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for Models 1 and 2, and parametrically using 200 repetitions for Model 3. Model 3 is estimated using 9 permanent and 3 time-varying heterogeneity mass points.
*** indicates significance at 1%, ** 5%, and * 10%. Coefficient from estimation are available in Appendix B.1.

Table 2.6: Five Year Prediction of Body Mass Status by Employment and Child Care (informal and formal) Alternatives

Employment and child care alternatives	Model 1c		Model 2c		Model 3	
Probability of Obese						
No work, no child care	18.75	(0.95)	20.42	(0.71)	20.02	(2.22)
No work, use child care (informal or formal)	20.70	(3.13)	20.98	(1.71)	18.62	(4.12)
Part-time, no child care	18.27	(1.08)	19.37	(0.72)	15.33	(1.51)
Part-time, informal child care	23.59	(2.61)	20.32	(1.27)	20.23	(3.39)
Part-time, formal child care	14.08	(2.89)	20.00	(1.71)	10.50	(5.06)
Full-time, no child care	19.19	(1.07)	18.81	(0.66)	12.73	(1.03)
Full-time, informal child care	20.89	(1.32)	19.35	(0.81)	15.21	(1.60)
Full-time, formal child care	21.81	(1.52)	19.72	(1.00)	15.56	(2.35)
Probability of Overweight						
No work, no child care	35.72	(1.21)	37.74	(0.85)	39.00	(2.70)
No work, use child care (informal or formal)	31.65	(4.00)	36.91	(1.97)	28.77	(5.38)
Part-time, no child care	35.29	(1.28)	35.84	(0.76)	37.54	(2.46)
Part-time, informal child care	39.02	(2.99)	37.51	(1.55)	35.15	(3.76)
Part-time, formal child care	29.54	(3.59)	36.71	(2.02)	43.86	(10.31)
Full-time, no child care	37.01	(1.26)	36.06	(0.73)	32.01	(2.11)
Full-time, informal child care	41.14	(1.67)	37.92	(0.97)	40.83	(2.76)
Full-time, formal child care	35.91	(1.99)	34.93	(1.07)	22.79	(2.94)
Predicted BMI						
No work, no child care	64.21	(0.64)	65.56	(0.51)	62.99	(0.69)
No work, use child care (informal or formal)	63.13	(2.17)	65.51	(1.03)	59.91	(1.45)
Part-time, no child care	64.77	(0.67)	64.78	(0.46)	61.17	(0.62)
Part-time, informal child care	67.46	(1.61)	64.90	(0.76)	126.39	(1.86)
Part-time, formal child care	60.21	(2.20)	64.51	(1.10)	68.41	(1.57)
Full-time, no child care	65.78	(0.73)	64.92	(0.47)	62.27	(0.59)
Full-time, informal child care	67.32	(0.78)	66.04	(0.54)	63.76	(0.73)
Full-time, formal child care	64.32	(1.04)	64.21	(0.66)	59.34	(1.02)

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for Models 1 and 2, and parametrically using 200 repetitions for Model 3.

Table 2.7: Five Year Simulation Differences on the Risk of Being Obese by Employment and Child Care (informal and formal) Alternatives

Employment and child care Alternatives	Model 1c		Model 2c		Model 3	
Compared to no work, no child care						
No work, use child care	1.949		0.006		-1.400	
(informal or formal care)	(3.340)		(1.685)		(4.425)	
Part-time, no child care	-0.479		-0.011		-4.694	*
	(1.315)		(0.693)		(2.600)	
Part-time, informal child care	4.847	*	-0.001		0.213	
	(2.704)		(1.269)		(4.114)	
Part-time, formal child care	-4.665		-0.004		-9.518	*
	(3.010)		(1.735)		(5.723)	
Full-time, no child care	0.441		-0.016		-7.294	***
	(1.433)		(0.817)		(2.693)	
Full-time, informal child care	2.147		-0.011		-4.807	*
	(1.535)		(0.990)		(2.928)	
Full-time, formal child care	3.060	*	-0.007		-4.463	
	(1.763)		(1.128)		(3.721)	
Compared to Full-time, no child care						
No work, no child care	-0.441		1.611	**	7.294	**
	(1.433)		(0.817)		(2.928)	
No work, use child care	1.509		2.174		5.894	
(informal or formal care)	(3.344)		(1.686)		(4.588)	
Part-time, no child care	-0.919		0.560		2.600	
	(1.350)		(0.707)		(2.399)	
Part-time, informal child care	4.407		1.513		7.508	**
	(2.886)		(1.223)		(3.586)	
Part-time, formal child care	-5.105	*	1.195		-2.224	
	(3.063)		(1.654)		(5.422)	
Full-time, informal child care	1.707		0.542		2.487	
	(1.630)		(0.716)		(2.766)	
Full-time, formal child care	2.620		0.909		2.832	
	(1.814)		(0.944)		(2.473)	

Table 2.7 (continued)

Employment and child care Alternatives	Model 1c		Model 2c	Model 3	
Compared to Full-time, informal child care					
No work, no child care	-2.147		1.069	4.807	*
	(1.535)		(0.990)	(2.928)	
No work, use child care	-0.198		1.632	3.407	
(informal or formal care)	(3.470)		(1.812)	(4.588)	
Part-time, no child care	-2.626	*	0.018	0.113	
	(1.613)		(0.855)	(2.399)	
Part-time, informal child care	2.700		0.971	5.020	
	(2.822)		(1.226)	(3.586)	
Part-time, formal child care	-6.812	**	0.653	-4.711	
	(3.090)		(1.612)	(5.422)	
Full-time, no child care	-1.707		-0.542	-2.487	
	(1.630)		(0.716)	(1.816)	
Full-time, formal child care	0.913		0.367	0.344	
	(2.049)		(1.075)	(2.766)	

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for Models 1 and 2, and parametrically using 200 repetitions for Model 3.

Table 2.8: Five Year Simulation Differences on the Risk of Being Overweight by Employment and Child Care (informal and formal) Alternatives

Employment and child care Alternatives	Model 1c		Model 2c		Model 3	
Compared to no work, no child care						
No work, use child care	-4.075		-0.832		-10.225	*
(informal or formal care)	(4.342)		(1.900)		(5.696)	
Part-time, no child care	-0.433		-1.902	**	-1.459	
	(1.738)		(0.904)		(3.373)	
Part-time, informal child care	3.299		-0.228		-3.841	
	(3.128)		(1.622)		(4.502)	
Part-time, formal child care	-6.185		-1.026		4.860	
	(3.878)		(2.122)		(11.144)	
Full-time, no child care	1.286		-1.682	*	-6.987	*
	(1.727)		(0.931)		(4.117)	
Full-time, informal child care	5.415	**	0.181		1.831	
	(2.222)		(1.123)		(4.254)	
Full-time, formal child care	0.190		-2.812	**	-16.210	***
	(2.257)		(1.315)		(4.367)	
Compared to Full-time, no child care						
No work, no child care	-1.286		1.682	*	6.987	*
	(1.727)		(0.931)		(4.117)	
No work, use child care	-5.361		0.850		-3.238	
(informal or formal care)	(4.186)		(1.905)		(6.041)	
Part-time, no child care	-1.719		-0.220		5.529	
	(1.869)		(0.847)		(3.470)	
Part-time, informal child care	2.014		1.455		3.147	
	(3.309)		(1.487)		(4.504)	
Part-time, formal child care	-7.471	**	0.656		11.847	
	(3.850)		(1.994)		(10.580)	
Full-time, informal child care	4.129	*	1.864	**	8.818	***
	(2.154)		(0.941)		(3.196)	
Full-time, formal child care	-1.096		-1.129		-9.222	**
	(2.366)		(1.171)		(3.621)	

Table 2.8 (continued)

Employment and child care Alternatives	Model 1c		Model 2c		Model 3	
Compared to Full-time, informal child care						
No work, no child care	-5.415	**	-0.181		-1.831	
	(2.222)		(1.123)		(4.254)	
No work, use child care	-9.490	**	-1.013		-12.056	**
(informal or formal care)	(4.306)		(1.961)		(6.111)	
Part-time, no child care	-5.848	***	-2.083	*	-3.289	
	(2.100)		(1.109)		(4.440)	
Part-time, informal child care	-2.116		-0.409		-5.672	
	(3.500)		(1.635)		(4.621)	
Part-time, formal child care	-11.600	***	-1.208		3.029	
	(3.851)		(2.003)		(10.958)	
Full-time, no child care	-4.129	*	-1.864	*	-8.818	***
	(2.154)		(0.941)		(3.196)	
Full-time, formal child care	-5.225	**	-2.993	**	-18.040	***
	(2.455)		(1.276)		(3.639)	

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for Models 1 and 2, and parametrically using 200 repetitions for Model 3.

Table 2.9: Five Year Simulation Differences on BMI-Percentile-for-Sex-and-Age by Employment and Child Care (informal and formal) Alternatives

Employment and child care Alternatives	Model 1c		Model 2c		Model 3	
Compared to no work, no child care						
No work, use child care	-1.079		-0.045		-3.081	**
(informal or formal)	(2.230)		(1.027)		(1.538)	
Part-time, no child care	0.554		-0.784	**	-1.817	***
	(0.852)		(0.384)		(0.691)	
Part-time, informal child care	3.243	**	-0.659		63.403	***
	(1.614)		(0.744)		(1.986)	
Part-time, formal child care	-4.003	*	-1.054		5.424	***
	(2.264)		(1.136)		(1.759)	
Full-time, no child care	1.564	*	-0.636		-0.720	
	(0.885)		(0.495)		(0.816)	
Full-time, informal child care	3.106	***	0.482		0.766	
	(0.918)		(0.553)		(0.975)	
Full-time, formal child care	0.106		-1.352	**	-3.646	***
	(1.176)		(0.693)		(1.151)	
Compared to Full-time, no child care						
No work, no child care	-1.564	*	0.636		0.720	
	(0.885)		(0.495)		(0.816)	
No work, use child care	-2.643		0.590		-2.362	
(informal or formal)	(2.188)		(1.044)		(1.548)	
Part-time, no child care	-1.010		-0.148		-1.097	
	(0.882)		(0.440)		(0.684)	
Part-time, informal child care	1.679		-0.023		64.122	***
	(1.719)		(0.719)		(1.858)	
Part-time, formal child care	-5.567	**	-0.419		6.144	***
	(2.317)		(1.072)		(1.618)	
Full-time, informal child care	1.541	*	1.117	***	1.486	**
	(0.944)		(0.432)		(0.753)	
Full-time, formal child care	-3.000	**	-1.834	***	-2.927	***
	(1.232)		(0.661)		(0.987)	

Table 2.9 (continued)

Employment and child care Alternatives	Model 1c		Model 2c		Model 3	
Compared to Full-time, informal child care						
No work, no child care	-3.106	***	-0.482		-0.766	
	(0.918)		(0.553)		(0.975)	
No work, use child care	-4.185	*	-0.527		-3.848	**
(informal or formal)	(2.363)		(1.110)		(1.593)	
Part-time, no child care	-2.552	***	-1.266	*	-2.583	***
	(0.934)		(0.527)		(0.865)	
Part-time, informal child care	0.137		-1.141		62.636	***
	(1.695)		(0.719)		(1.956)	
Part-time, formal child care	-7.108	***	-1.536		4.658	***
	(2.231)		(1.114)		(1.734)	
Full-time, no child care	-1.541	*	-1.117	***	-1.486	**
	(0.944)		(0.432)		(0.753)	
Full-time, formal child care	-3.000	**	-1.834	***	-4.412	***
	(1.232)		(0.661)		(1.022)	

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for Models 1 and 2, and parametrically using 200 repetitions for Model 3.

Table 2.10: Descriptive Statistics of Cognitive Status by Employment and Child Care Alternatives

Employment and child care Alternatives	N	Reading Score	Math Score
No work, no child care	5056	53.28	53.10
No work, use child care (informal or formal)	295	49.21	48.79
Part-time, no child care	4629	54.29	54.28
Part-time, informal child care	782	52.03	52.12
Part-time, formal child care	383	53.89	54.11
Full-time, no child care	4485	52.45	52.32
Full-time, informal child care	2779	51.31	51.27
Full-time, formal child care	1613	53.30	53.08
Overall	20022	53.00	52.90

Table 2.11: Marginal Effect of Maternal Employment and Child Care Alternatives on Reading Scores

	Exogenous			Individual Fixed Effect			Joint
Employment and child care alternatives	Model 1a	Model 1b	Model 1c	Model 2a	Model 2b	Model 2c	Model 3
No work, no child care	Omitted Category						
No work, use child care	-4.073 ***	-1.162 **	-0.485	-0.333	-0.311	-0.271	0.121
(informal or formal)	(0.585)	(0.537)	(0.353)	(0.437)	(0.372)	(0.422)	(0.530)
Part-time, no child care	1.012 ***	-0.130	-0.002	0.185	0.147	0.145	0.187
	(0.177)	(0.165)	(0.114)	(0.179)	(0.171)	(0.165)	(0.250)
Part-time, informal child care	-1.243 ***	-0.696 **	-0.419 **	-0.162	-0.150	-0.183	-0.513
	(0.335)	(0.309)	(0.201)	(0.296)	(0.314)	(0.284)	(0.554)
Part-time, formal child care	0.614	-0.092	-0.477 *	-0.622	-0.555	-0.591	-1.035
	(0.450)	(0.428)	(0.272)	(0.421)	(0.395)	(0.407)	(0.701)
Full-time, no child care	-0.830 ***	-0.813 ***	-0.339 ***	0.031	-0.035	-0.058	-0.253
	(0.157)	(0.184)	(0.123)	(0.182)	(0.199)	(0.190)	(0.341)
Full-time, informal child care	-1.968 ***	-1.035 ***	-0.481 ***	-0.201	-0.172	-0.188	-0.276
	(0.214)	(0.202)	(0.144)	(0.241)	(0.201)	(0.238)	(0.405)
Full-time, formal child care	0.021	-0.459 **	-0.451 ***	-0.349	-0.264	-0.281	-0.550
	(0.263)	(0.232)	(0.142)	(0.261)	(0.265)	(0.260)	(0.390)
Controls for:							
Exogenous characteristics	No	Yes	Yes	No	Yes	Yes	Yes
Lagged cognitive	No	No	Yes	No	No	Yes	Yes

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for Models 1 and 2, and parametrically using 200 repetitions for Model 3. Model 3 is estimated using 10 permanent and 3 time-varying heterogeneity mass points.
*** indicates significance at 1%, ** 5%, and * 10%. Coefficient from estimation available in Appendix B.1.

Table 2.12: Marginal Effect of Maternal Employment and Child Care Alternatives on Math Scores

	Exogenous			Individual Fixed Effect			Joint
Employment and child care alternatives	Model 1a	Model 1b	Model 1c	Model 2a	Model 2b	Model 2c	Model 3
No work, no child care	Omitted Category						
No work, use child care	-4.312 ***	-0.994 *	-0.528	0.074	0.197	0.142	0.145
(informal or formal)	(0.588)	(0.566)	(0.355)	(0.365)	(0.443)	(0.388)	(0.438)
Part-time, no child care	1.172 ***	0.093	0.038	0.270 *	0.243	0.241 *	0.165
	(0.176)	(0.162)	(0.095)	(0.155)	(0.161)	(0.155)	(0.234)
Part-time, informal child care	-0.987 ***	-0.183	0.056	0.066	0.040	0.001	-0.100
	(0.358)	(0.322)	(0.200)	(0.269)	(0.273)	(0.257)	(0.478)
Part-time, formal child care	1.009 **	0.508	0.275	0.216	0.257	0.277	-0.476
	(0.454)	(0.381)	(0.306)	(0.396)	(0.421)	(0.355)	(0.648)
Full-time, no child care	-0.780 ***	-0.650 ***	-0.198 *	0.071	0.028	0.011	-0.085
	(0.183)	(0.169)	(0.109)	(0.173)	(0.181)	(0.172)	(0.284)
Full-time, informal child care	-1.836 ***	-0.677 ***	-0.192	0.015	0.060	0.023	0.069
	(0.199)	(0.201)	(0.146)	(0.202)	(0.194)	(0.186)	(0.356)
Full-time, formal child care	-0.025	-0.143	-0.227	-0.156	-0.025	-0.058	-0.379
	(0.248)	(0.263)	(0.151)	(0.248)	(0.253)	(0.224)	(0.373)
Controls for:							
Exogenous characteristics	No	Yes	Yes	No	Yes	Yes	Yes
Lagged cognitive	No	No	Yes	No	No	Yes	Yes

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for Models 1 and 2, and parametrically using 200 repetitions for Model 3. Model 3 is estimated using 10 permanent and 3 time-varying heterogeneity mass points.
*** indicates significance at 1%, ** 5%, and * 10%. Coefficient from estimation available in Appendix B.1.

Table 2.13: Five Year Prediction of Cognitive Outcomes by Employment and Child Care Alternatives

Employment and child care alternatives	Model 1c		Model 2c		Model 3	
Predicted Reading Scores						
No work, no child care	53.68	(0.19)	53.20	(0.16)	53.38	(0.37)
No work, use child care (informal or formal)	52.51	(0.80)	52.89	(0.38)	53.61	(0.90)
Part-time, no child care	53.66	(0.18)	53.35	(0.14)	53.70	(0.31)
Part-time, informal child care	52.72	(0.44)	53.00	(0.22)	52.49	(0.80)
Part-time, formal child care	52.50	(0.57)	52.57	(0.40)	51.51	(1.19)
Full-time, no child care	52.90	(0.20)	53.16	(0.15)	52.93	(0.35)
Full-time, informal child care	52.58	(0.22)	53.01	(0.17)	52.89	(0.51)
Full-time, formal child care	52.65	(0.31)	52.91	(0.22)	52.37	(0.50)
Predicted Math Scores						
No work, no child care	53.24	(0.19)	52.99	(0.15)	53.04	(0.32)
No work, use child care (informal or formal)	52.03	(0.89)	53.10	(0.34)	53.30	(0.71)
Part-time, no child care	53.33	(0.18)	53.20	(0.13)	53.33	(0.29)
Part-time, informal child care	53.34	(0.44)	52.99	(0.22)	52.87	(0.72)
Part-time, formal child care	53.83	(0.56)	53.18	(0.28)	52.27	(1.00)
Full-time, no child care	52.74	(0.18)	53.00	(0.14)	52.89	(0.31)
Full-time, informal child care	52.78	(0.25)	53.01	(0.16)	53.16	(0.46)
Full-time, formal child care	52.70	(0.32)	52.93	(0.19)	52.34	(0.51)

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for Models 1 and 2, and parametrically using 200 repetitions for Model 3.

Table 2.14: Five Year Simulation Differences on Reading Scores by Employment and Child Care (informal and formal) Alternatives

Employment and child care Alternatives	Model 1c		Model 2c	Model 3	
Compared to no work, no child care					
No work, use child care (informal or formal)	-1.165		-0.314	0.225	
	(0.819)		(0.391)	(0.945)	
Part-time, no child care	-0.015		0.153	0.322	
	(0.229)		(0.142)	(0.440)	
Part-time, informal child care	-0.955	**	-0.200	-0.887	
	(0.466)		(0.234)	(0.948)	
Part-time, formal child care	-1.175	**	-0.634	-1.874	
	(0.603)		(0.405)	(1.267)	
Full-time, no child care	-0.773	***	-0.037	-0.450	
	(0.254)		(0.171)	(0.610)	
Full-time, informal child care	-1.096	***	-0.188	-0.489	
	(0.273)		(0.196)	(0.720)	
Full-time, formal child care	-1.029	***	-0.290	-1.009	
	(0.349)		(0.244)	(0.713)	
Compared to Full-time, no child care					
No work, no child care	0.773	***	0.037	0.450	
	(0.254)		(0.171)	(0.610)	
No work, use child care (informal or formal)	-0.392		-0.276	0.675	
	(0.808)		(0.393)	(0.935)	
Part-time, no child care	0.758	***	0.191	0.771	
	(0.254)		(0.137)	(0.553)	
Part-time, informal child care	-0.183		-0.163	-0.438	***
	(0.486)		(0.240)	(0.873)	
Part-time, formal child care	-0.402		-0.597	-1.424	***
	(0.596)		(0.402)	(1.267)	
Full-time, informal child care	-0.323		-0.150	0.039	**
	(0.287)		(0.156)	(0.612)	
Full-time, formal child care	-0.256		-0.253	-0.039	**
	(0.348)		(0.194)	(0.612)	

Table 2.14 (continued)

Employment and child care Alternatives	Model 1c		Model 2c		Model 3	
Compared to Full-time, informal child care						
No work, no child care	1.096	***	0.188		0.489	
	(0.273)		(0.196)		(0.720)	
No work, use child care	-0.069		-0.126		0.714	*
(informal or formal)	(0.814)		(0.415)		(1.052)	
Part-time, no child care	1.081	***	0.341	*	0.810	
	(0.279)		(0.183)		(0.679)	
Part-time, informal child care	0.140		-0.012		-0.398	***
	(0.505)		(0.252)		(0.888)	
Part-time, formal child care	-0.079		-0.446		-1.385	***
	(0.605)		(0.414)		(1.337)	
Full-time, no child care	0.323		0.150		0.039	**
	(0.287)		(0.156)		(0.612)	
Full-time, formal child care	0.067		-0.102		-0.520	**
	(0.369)		(0.208)		(0.659)	

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for Models 1 and 2, and parametrically using 200 repetitions for Model 3.

Table 2.15: Five Year Simulation Differences on Math Scores by Employment and Child Care (informal and formal) Alternatives

Employment and child care Alternatives	Model 1c		Model 2c		Model 3
Compared to no work, no child care					
No work, use child care	-1.209		0.110		-0.255
(informal or formal)	(0.900)		(0.334)		(0.755)
Part-time, no child care	0.089		0.213	*	0.288
	(0.246)		(0.115)		(0.411)
Part-time, informal child care	0.101		-0.001		-0.172
	(0.474)		(0.197)		(0.832)
Part-time, formal child care	0.594		0.190		-0.774
	(0.570)		(0.283)		(1.059)
Full-time, no child care	-0.496	**	0.007		-0.154
	(0.246)		(0.140)		(0.509)
Full-time, informal child care	-0.456		0.023		0.121
	(0.301)		(0.161)		(0.620)
Full-time, formal child care	-0.535		-0.056		-0.702
	(0.357)		(0.181)		(0.680)
Compared to Full-time, no child care					
No work, no child care	0.496	**	-0.007		0.154
	(0.246)		(0.140)		(0.509)
No work, use child care	-0.713		0.103		0.408
(informal or formal)	(0.905)		(0.320)		(0.749)
Part-time, no child care	0.585	**	0.206	*	0.441
	(0.238)		(0.124)		(0.488)
Part-time, informal child care	0.596		-0.008		-0.018
	(0.464)		(0.203)		(0.791)
Part-time, formal child care	1.090	**	0.183		-0.621
	(0.564)		(0.282)		(1.056)
Full-time, informal child care	0.040		0.016		0.275
	(0.288)		(0.127)		(0.535)
Full-time, formal child care	-0.039		-0.063		-0.549
	(0.351)		(0.145)		(0.547)

Table 2.15 (continued)

Employment and child care Alternatives	Model 1c		Model 2c	Model 3
Compared to Full-time, informal child care				
No work, no child care	0.456		-0.023	-0.121
	(0.301)		(0.161)	(0.620)
No work, use child care	-0.753		0.087	0.134
(informal or formal)	(0.912)		(0.328)	(0.854)
Part-time, no child care	0.546	*	0.191	0.167
	(0.297)		(0.138)	(0.614)
Part-time, informal child care	0.557		-0.023	-0.293
	(0.468)		(0.208)	(0.797)
Part-time, formal child care	1.051	*	0.167	-0.895
	(0.606)		(0.271)	(1.140)
Full-time, no child care	-0.040		-0.016	-0.275
	(0.288)		(0.127)	(0.535)
Full-time, formal child care	-0.079		-0.078	-0.823
	(0.403)		(0.164)	(0.624)

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for Models 1 and 2, and parametrically using 200 repetitions for Model 3.

Chapter 3

Maternal Employment, Child Care, and Child Health: An Alternative Empirical Approach

3.1 Introduction

Childhood obesity rates in the United States have increased dramatically since the late 1970s. Between 1976 and 2004, obesity rates increased from 6 to 19 percent for children ages 6 to 11 and from 5 to 17 percent for young adults ages 12 to 17 (Centers for Disease Control and Prevention, 2007) according to analysis of data from the National Health and Nutrition Examination Survey (NHANES). As the physical health of children in the United States has deteriorated, researchers have examined the effects of various determinants on children's overweight and obesity risk. However, many such studies have not analyzed the effect of such variables along the entire distribution of children's body mass status. That is, do relevant factors have a different effect on children of different body mass status? To this end, I highlight the importance of appropriately capturing the *distribution* of the body mass status outcome in this analysis. Specifically, I estimate the density function of body mass status using a discrete approximation, allowing the covariates to have differing effects along the support of the distribution. I find that the effect of full-time employment with no child care has very little effect (compared to not working and not using child care).

For adults, obesity or overweight status is often defined using a standardized measure called

Body Mass Index (referred from this point on as BMI), which is simply a ratio of weight in kilograms to height in meters squared. The Centers for Disease Control and Prevention (CDC) then defines individuals as being overweight if their BMI is between 25 and 30; obese, if their BMI is between 30 and 35; and morbidly obese, if their BMI is greater than 35. One of the criticisms against BMI, despite being widely used in the literature, is that it fails to capture many individuals' characteristics such as musculature and genetics that might, by the CDC standards, categorize individuals into a body mass group that may not necessarily capture their overall physical healthiness.

Children's body mass statuses are defined in a slightly different manner to reflect changes in children's weight and height due to growth. In 1977, growth charts were developed by the National Centers for Health Statistics (NCHS) using the National Health and Nutrition Examination Survey (NHANES). These growth charts, which were updated in 2000, allow medical professionals to track children's growth in comparison to children of the same sex- and age-group. More specifically, a child's BMI (weight in kilograms over height in meters squared) is converted into a standard score (more commonly known as a z-score, Z), which is the difference in the child's BMI and the age-and-sex-specific population mean, in standard deviation units. That is

$$Z = \frac{BMI - \mu_{ag}}{\sigma_{ag}} \tag{3.1}$$

where BMI is an individual's BMI, μ_{ag} and σ_{ag} are age (a) and gender (g) specific mean and standard deviations, respectively. To convert children's standard scores into percentiles, the CDC's guidelines assume that the underlying population's BMI is normally distributed. According to the CDC, children with a BMI-percentile-for-age-and-sex greater than the 85th percentile are overweight, and greater than the 95th percentile are obese. One of the key issues in using BMI-percentile-for-age-and-sex percentiles as a measure of a child's body mass status is the restrictiveness of the distributional assumption that the z-score has a normal distribution.

In this paper, I examine the impact of two notable changes that occurred during the same time period as the increase in childhood overweight and obesity: an increase in women's labor force participation and in the usage of child care. I control for both observed and unobserved permanent and time-varying individual heterogeneity to account for possible biases introduced through endogeneity issues. More importantly, I relax the distributional assumption about the body mass status outcome by approximating a discrete distribution of the health outcome. To this end, the impact of maternal employment and child care on elementary school-age children's body mass status is studied, allowing the effects to differ across the body mass distribution using a technique called the Conditional Density Estimation (CDE) method. I begin by introducing the econometric issue in Section 3.2. In Section 3.3, I described the empirical model and briefly describe the data. Results are presented in Section 3.5 and Section 3.6 concludes.

3.2 Background

In many situations (especially in health research), the distribution of an outcome that researchers are interested in studying can be highly skewed. For example, outcomes such as medical care expenditures or alcohol consumption can have a large number of observations at zero and can also be highly skewed to the right. In such cases it has been popular to transform the data using a log-transformation and employ two part modeling techniques.

Of particular interest to researchers and policymakers may not be the actual distribution of the outcome, but rather evaluation of the impact of covariates on the expectation of an outcome. For example, suppose that a researcher is interested in examining the impact of a variable x on the expected value of an outcome Y, $E(Y|x)$. If Y is a continuous outcome, the expectation of Y conditional on x is

$$E(Y|x) = \int_{-\infty}^{\infty} y \cdot f(y|x)\mathrm{d}y \tag{3.2}$$

where $f(y|x)$ is the probability density function (pdf) of a random variable Y conditional on covariate x. If the outcome, Y, is discrete, then the expectation of the outcome, conditional on the covariates (x) is

$$E(Y|x) = \sum_{y=-\infty}^{\infty} y \cdot f(y|x) \tag{3.3}$$

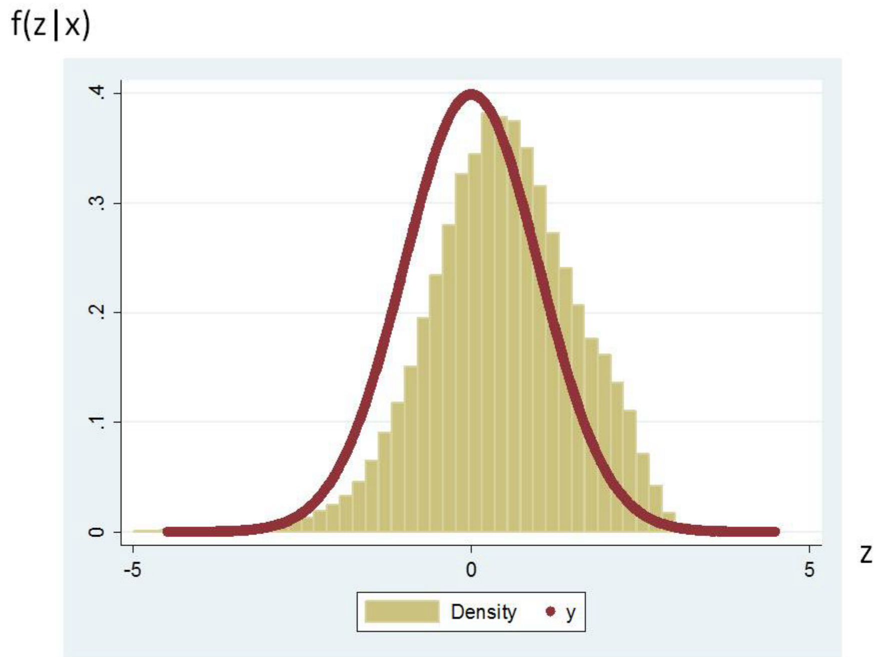
In this analysis, where I am interested in estimating the impact of mother's joint employment and child care decisions on the body mass status of elementary school-age children, it is of interest to correctly define the distribution of the body mass status outcome. The current research indicates that the distribution of age-and-sex-specific BMI has changed over the past three decade. Specifically, the right tail of the distribution has greater mass which suggests that children who were overweight or obese have become heavier (compared to the entire population becoming heavier, which would have implied a shift in the entire BMI distribution to the right). Despite such evidence, much of the current research assumes that the body mass status of children is normally distributed.

In Figure 3.1, I present the probability distribution function of z-scores (the measure of body mass status) used in my analysis and compare this to a normal distribution. I find that the distribution of body mass status of the children in the ECLS-K is skewed to the right, suggesting that over the past three decades the body mass status of young children has changed, but not uniformly across the entire distribution. Rather, the increase in body mass status seems to have been greater for individuals in the right tail of the distribution. Therefore, this suggests that the health outcome may not necessarily be normally distributed.

A large body of literature discusses alternative distributional assumptions that can be applied when the data do not exhibit a typical normal distribution. However, work by Gilleskie and Mroz (2004) allows the researcher to avoid making such difficult modeling choices by estimating a discretized distribution of the density. The Conditional Density Estimation (CDE) procedure breaks the density of a random variable into K discrete intervals, where the appropriate number of intervals is determined within the estimation procedure. The researcher then estimates the probability that a random variable falls into the k^{th} interval conditional on not having fallen into the first $k-1$ intervals and can then subsequently estimate the unconditional probability of falling into an interval. The expectation of any function of the random variable of interest is then estimated by taking a weighted (by the probability of being in an interval) sum.

Specifically for this analysis, where the outcome of interest is the body mass status, which I measure using Z-scores and is described in greater detail in Section 3.3, observations can be divided into k intervals. The probability that the body mass outcome falls in the k^{th} interval,

Figure 3.1: Distribution of Body Mass Status



conditional on not being in the first $k-1$ intervals is expressed as

$$\lambda(k,x) = \Pr\left[b_{k-1} \leq B_i < b_k \middle| \, x_i, B_i \geq b_{k-1}\right] = \frac{\int_{b_{k-1}}^{b_k} f(b|x)\mathrm{d}b}{1 - \int_{b_0}^{b_{k-1}} f(b|x)\ \mathrm{d}b} \tag{3.4}$$

Thus, the unconditional probability that the outcome falls in an interval is

$$\Pr\left[b_{k-1} \leq B_i < b_k | x\right] = \lambda(k,x) \prod_{j=1}^{k-1} \left[1 - \lambda(j,x)\right] \tag{3.5}$$

The expectation of any function $g(\cdot)$ of B is defined as

$$\begin{aligned} E(g(B)|x) &= \int_{-\infty}^{\infty} g(b) f(b|x)\mathrm{d}o \\ &\approx \sum_{k=1}^{K} g^*(k|K)\lambda(k,x) \prod_{j=1}^{k-1} [1 - \lambda(j,x)] \end{aligned} \tag{3.6}$$

where $g^*(\cdot)$ is an approximation of the function $g(\cdot)$. It should be noted that this approximation is not a function of x (Gilleskie and Mroz, 2004). The marginal effect, or impact of changes in x on the expectation is

$$\frac{\partial E(g(B)|x)}{\partial x} = \sum_{k=1}^{K} g^*(k|K) \left\{ \frac{\partial \lambda(k,x) \prod_{j=1}^{k-1}[1-\lambda(j,x)]}{\partial x} \right\} \tag{3.7}$$

3.2.1 Overview

This paper provides additional evidence of the impact of mothers' employment and child care decisions on children's body mass status and I again compare the effects of alternative types of child care (informal versus formal). I contribute to the current literature by: first, relaxing distributional assumptions about the body mass status outcome and allowing the effects of the joint employment and child care decision to differ along the support of the body mass status distribution and second, controlling for both permanent and time-varying unobservable variables that may be correlated with the joint employment and child care decision and child health.

3.3 Data and Empirical Model

3.3.1 Empirical Model

I begin by specifying an equation for the joint employment and child care decision, and an equation for the probability that the body mass outcome falls in the k^{th} interval, conditional on not having been in the first $k-1$ intervals (referred to from this point on as the hazard equation). In this analysis, I use two alternative combinations of employment and child care. In the first, I define child care as the total number of hours of child care (informal and formal) used (this follows from the analysis in Chapter 1), and in the second I differentiate between informal and formal child care to see if there are differences in the effect of child care by mode of care (this follows from the analysis in Chapter 2). For simplicity, I assume for now that the former definition of child care is of interest and collapse the employment and child care decisions into six mutually exclusive combinations:

$$d = \begin{cases} 0 & \text{if Not working and not using child care} \\ 1 & \text{if Not working and using child care} \\ 2 & \text{if Working part-time and not using child care} \\ 3 & \text{if Working part-time and using child care} \\ 4 & \text{if Working full-time and not using child care} \\ 5 & \text{if Working full-time and using child care} \end{cases} \tag{3.8}$$

where $D_t = d$ represents the joint employment and child care decision. Individuals not working are defined as those working between zero and eight hours per week, part-time if working between eight and thirty five hours per week, and full-time if working more than 35 hours per week. Individuals are defined as using child care if they use either informal (i.e., child care provided by a relative, siblings, or babysitter) or formal child care (i.e., child care in a facility that is not in one's home) for more than five hours per week.

In estimation, I consider an endogeneity issue where unobservable characteristics of the mother or child influences the mother's employment and child care decisions, and also the hazard equation (i.e., an equation for the probability that the body mass outcome falls in the k^{th} interval, conditional on not having been in the first $k-1$ intervals). I resolve this issue by jointly estimating an equation representing the joint demand for employment and child care, with the hazard equation allowing the error components in the two equations to be correlated. As such, two sources of unobserved heterogeneity can be captured: a permanent (μ) and a time-varying (ν_t) component. The decomposed error terms in the joint employment and child care decision equation, ϵ_{1t}^d, and the error terms in the hazard equation are:

$$\begin{aligned} \epsilon_{1t}^d &= \mu_1^d + \nu_{1t}^d + e_{1t}^d \quad \forall d = 0, ..., 5 \\ \epsilon_{2t} &= \mu_2 + \nu_{2t} + e_{2t}, \end{aligned}$$

where μ and ν_t capture the time-invariant and time-varying sources of unobserved heterogeneity, respectively, and e_{1t}^d and e_{2t} are the remaining error components that are identically and independently distributed.

The employment and child care decision, assuming that e_{1t} is Type-I Extreme Value distributed, conditional on the unobserved heterogeneity components (μ and ν_t), is written in log odds as

$$\ln\left[\frac{\Pr(D_t = d|\mu_1, \nu_{1t})}{\Pr(D_t = 0|\mu_1, \nu_{1t})}\right] = \gamma_{0d} + \gamma_{1d}B_t + \gamma_{2d}X_t + \gamma_{3d}P_t + \gamma_{4d}Z_t + \mu_1^d + \nu_{1t}^d \quad d = 1, ..., 5 \tag{3.9}$$

where the decisions are functions of body mass status entering the period (B_t), exogenous variables (X_t and P_t), and exclusion restrictions (Z_t).[1]

The probability that a child's body mass status (B_{t+1}) falls into the kth interval, given that it did not fall in one of the first k-1 intervals is

$$\lambda(k, x) = \Pr[B_{k-1} \leq B_{t+1} < B_k | B_{t+1} \geq B_{k-1}]. \tag{3.10}$$

I assume that the equation can be specified as a logit function.

The estimation technique employed is a joint estimation method, the discrete factor method (DFM), that allows for the possible correlation of the error terms across the employment and child care decision and hazard equations. Distributional assumptions about the error terms do not have to be made in this technique since the unobserved heterogeneity components are approximated using step-wise distributions.

The unconditional likelihood function for individual i is

$$\begin{aligned} L_i(\Theta, \psi, \pi) \quad = \quad & \sum_{k=1}^{K} \pi_k \Bigg\{ \phi(B_1|\mu_{2k}) \prod_{t=1}^{T} \sum_{\ell=1}^{L} \psi_\ell \Bigg[\prod_{d=0}^{5} Pr(D_t = d|\mu_{1k}^d, \nu_{1t\ell}^d) 1 \cdot [D_{it} = d] \times \\ & \prod_{m=1}^{M} \Big[\lambda(m, x|\mu_{2k}, \nu_{2t\ell}) \prod_{n=1}^{m-1} (1 - \lambda(n, x|\mu_{2k}, \nu_{2t\ell})) \Big] \Bigg] \Bigg\} \end{aligned} \tag{3.11}$$

where Θ is the vector of variables in the model that are to be estimated and ϕ is the probability density function for a normal distribution (for initial body mass status). The probabilities of the

[1]Further detail on the exogenous variables are available in Tables 1.1 and 1.2

discrete distributions of the unobserved time-invariant (μ) and time-varying (ν_t) heterogeneity are respectively given by

$$\pi_k = Pr(\mu_1^0 = \mu_{1k}^0, ..., \mu_1^5 = \mu_{1k}^5, \mu_2 = \mu_{2k}) \quad k = 1, ..., K$$
$$\psi_\ell = Pr(\nu_1 t^0 = \nu_{1t\ell}^0, ..., \nu_1 t^5 = \nu_{1t\ell}^5, \nu_2 t = \nu_{2t\ell}) \quad \ell = 1, ..., L, \forall t$$

where K is the number of time-invariant mass points and L is the number of time-varying mass points.[2]

3.3.2 Data

The data for this analysis come from the Early Childhood Longitudinal Study, Kindergarten Class of 1998 (ECLS-K) as in Chapters 1 and 2. This nationally representative survey of 21,409 kindergartners in 1998 began in the fall school year of 1998 (wave I). To date, this longitudinal survey has followed these children up until the eighth grade (interviews were conducted in the fall and spring of kindergarten, fall and spring of first grade, and the spring of third, fifth, and eighth grades). The survey includes detailed information on the child's emotional, cognitive, and psychological well-being; the child's home environment, as reported by parents/guardians; and the child's school characteristics and environment, as reported by the child's primary teacher. Furthermore, I am able to merge county- and state-level characteristics with each individual child using the child's residential zipcode that are available with a contract with the U.S. Department of Education. For the purposes of this paper, I restrict my attention to three survey years, 1999-2000, when most of the children were in first grade; 2001-2002, when most of the children were in third grade; and 2003-2004, when most of the children were in fifth grade.

The key variables used in this analysis are the employment and child care variables (defined in more detail in Chapter 1 and 2) and the body mass status measure. I construct the body mass status measure using the height and weight measures provided in the data. A child's BMI is estimated and then standardized to his/her age- and sex-group (see equation 3.1). Other variables that are used in analysis are described in greater detail in Chapter 1 and thus I do

[2] A more in depth discussion of the empirical estimation is available in Appendix C.1

not describe the variables in further detail in this section.

3.4 Results

3.4.1 Estimation Results

In this section, I begin by showing short run effects (i.e., marginal effects) of the employment and child care alternatives on body mass status. In Table 3.1, I present marginal effects of alternative employment and child care decisions on body mass status and in Table 3.4, I present marginal effects where I differentiate between informal and formal child care. In these tables I compare the results from models that do not control for unobserved heterogeneity to those that control for time-invariant and time-varying unobservable heterogeneity.

Results not controlling for unobserved heterogeneity

In Tables 3.1 and 3.5, I present short run effects of the employment and child care alternatives on body mass status. The first column (OLS) estimates the body mass status function as a linear regression model. The second column (CDE) estimates the body mass status function using the conditional density estimation technique. Both models control for exogenous child, mother and father characteristics (X_t), community characteristics (P_t), and lagged health (B_t). However, the models do not control for possible unobserved characteristics that may be correlated with the employment and child care decision and child health. Standard errors (in parentheses) are non-parametrically bootstrapped using 200 draws.

In the first column (OLS) of Table 3.1, I find that full-time employment (regardless of child care) increases children's z-scores compared to not working and not using child care. That is, full-time employment without child care increases z-scores by around 0.02 points and full-time employment with child care by around 0.04 points. In the second column (CDE) of Table 3.1, where I allow for the covariates to have differing effects along the support of the distribution, I find that all of the alternatives, except for no work and using child care, increases body mass status compared to not working and not using child care. For instance, the effect of full-time employment with no child care, which is greater than in the first column, increases z-scores by 0.034 points. Full-time employment with child care also significantly increases z-scores by around 0.032 points.

Similarly in Table 3.5, where I differentiate between types of child care (informal versus formal) I find that with the OLS model the effect of full-time employment with informal child care (compared to not working and not using child care) increases z-scores by around 0.05 points. I also find similar effects with the CDE model. The impact of full-time employment with no child care increases from 0.02 points to 0.03 points as I go from the OLS model to the CDE model. These results, that *do not* control for possible unobservable variables that my be correlated with the employment and child care decision and children's health, suggest that the effect of full-time employment with informal child care is more detrimental than using formal child care. Failure to control for such unobservables, however, may confound the effect of employment and child care on body mass status.

Results controlling for unobserved heterogeneity

In the third columns (DFM & CDE) of Tables 3.1 and 3.5, I present marginal effects from the preferred model that controls for unobserved heterogeneity. Standard errors (in parentheses) are parametrically bootstrapped using 200 draws. In both tables, controlling for unobserved heterogeneity significantly alters the results. For example, in Table 3.1, I find that failure to control for unobserved heterogeneity underestimates the impact of full-time employment and child care, which significantly increases z-scores by 0.11 points (compared to not working and not using child care). In Table 3.5, I also find that the failure to control for unobserved heterogeneity underestimates the impact of full-time employment with no child care and full-time employment using informal child care. For example, the effect of full-time employment with informal child care increases from 0.05 to 0.11 when comparing the CDE model to the preferred model (CDE & DFM). It is also interesting to note that the effects of full-time employment with no child care are insignificant in both tables. These results provide evidence of unobservable variables influencing both the employment and child care decision and child health.

3.4.2 Simulation Results

The results presented in the previous section are short-run effects of the employment and child care alternatives. In this dynamic framework I am able to capture the long run effect of alternative employment and child care choices through simulations. To conduct the simulations, I generate 5 replications of each individual and allow each replication a draw from the unobserved heterogeneity distribution. Using observed body mass status in kindergarten, I assign individuals to an employment and child care category and simulate the hazard. Using the predicted hazard, I again draw from a distribution to predict the likelihood of their being in a particular cell. The mean of the cell is used to update the child's body mass status at the end of the period and this process is repeated for the third and fifth grades.

Long run effects with and without unobserved heterogeneity

In Tables 3.2 and 3.6, I present five year simulations of predicted z-scores for a model that does not differentiate between modes of child care and for a model that differentiates between informal and formal child care, respectively. Both tables present predicted z-scores for three models: OLS, which assumes the the z-score is a linear function of observable characteristics; CDE, which also controls for observable characteristics and also allow the employment and child care alternatives to have different effects along the support of the distribution; and CDE & DFM, which controls for potential unobservable characteristics. In Table 3.2, I find that failure to control for potential unobservable characteristics results in an underbias of the impact of employment and child care.

In Tables 3.3. and 3.7, I present differences in the long run effects. The upper rows compare the employment and child care alternatives to no work and no child care, the middle rows to full-time work with no child care, and the last rows to full-time work with informal child care. Once again, I compare the differences across three models, two which only control for observable characteristics and a preferred model that controls for observed and unobserved heterogeneity. In Table 3.3, I find that compared to not working and not using child care the first two models, that do not control for unobserved heterogeneity, would suggest that full-time work (regardless of child care) increases z-scores. However, results from the preferred model suggest that the there is no effect of full-time employment with no child care in the long-run. Full-time employment with child care, on the other hand, increases z-scores by around 0.24 points. In Table 3.7, I find that compared to full-time employment with no child care, full-time employment with informal child care significantly increases z-scores by around 0.38 points. On the other hand, full-time employment with formal child care is not significantly different from full-time employment with no child care.

Differences in the long run effects by initial body mass status

In Tables 3.4 and 3.8, I report predicted z-scores, by the child's body mass status in kindergarten. Specifically, the long run effects of the alternatives are reported for children who were obese (z-score $\geq$ 1.645), overweight (z-score $\geq$ 1.036, but $<$ 1.036) and normal weight (z-score $<$ 1.036). In Table 3.4, I find that, full-time employment with child care (compared to no work and no child care) increases z-scores by 4.7% for children who were obese, 9.0% for children who were overweight, and by 90% for children who were of normal weight. When I compare full-time employment with child care to full-time employment with no child care, I find that using child care increases z-score by less that 1% for children who were obese, by 4.6% for children who were overweight, and by 47% for children who were normal weight. Overall, these findings suggest that the detrimental effect of child care (for full-time workers) is greater for children of normal weight.

In Table 3.8, I find similar results. Specifically, full-time employment with informal child care (compared to full-time work and no child care) increases z-scores by 2.5% for obese children, 8.8% for overweight children, and 87.4% for normal weight children. Once again, the detrimental effect of informal child care (for full-time workers) is greater for children of normal weight.

3.5 Discussion and Summary

Methods of classifying the body mass status of individuals has received considerable attention by researchers and policymakers. Much of the current research uses BMI as a measure of one's physical health and many assume that children's body mass status can be described as a normal distribution. In this paper, I contribute to the current literature by relaxing the distributional assumptions about body mass status. I find that full-time employment with child care (compared to not working and not using child care) has a detrimental effect on children' z-scores. Furthermore, by separating child care into informal and formal child care, I find that the detrimental effect of child care may be driven by informal child care. Specifically, informal child care has a detrimental effect on z-scores, but formal child care does not seem to have a significant impact.

Overall, this analysis is the first step in examining the role of mothers' employment and child care decisions on children's health, allowing for the determinants to have differing effects along the distribution of the outcome. Furthermore, I extend the analysis to control for potential time-invariant and time-varying unobservables that may be correlated with the employment and child care decision and child health. I provide an alternative estimation technique to researchers evaluating the current obesity epidemic that allows determinants to have alternative roles along the points of support of the body mass outcome. As such, this technique can be easily applied to obesity literature for adults and may provide greater insight into the role of various social, economic, and environmental determinants on the current obesity epidemic.

Table 3.1: Marginal Effect of Maternal Employment and Child Care Alternatives on Body Mass Status

Employment and child care alternatives	Exogenous OLS		Exogenous CDE		Joint DFM & CDE	
No work, no child care	Omitted Category					
No work, using child care	-0.012		-0.008		-0.748	***
	(0.037)		(0.006)		(0.163)	
Part-time, no child care	0.008		0.014	***	0.183	
	(0.013)		(0.003)		(0.150)	
Part-time, using child care	0.007		0.020	***	-0.012	
	(0.020)		(0.005)		(0.090)	
Full-time, no child care	0.019		0.034	***	0.036	
	(0.013)		(0.003)		(0.089)	
Full-time, using child care	0.035	**	0.032	***	0.111	**
	(0.015)		(0.003)		(0.058)	

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for the exogenous models and parametrically using 200 repetitions for the joint model. Model 3 is estimated using 6 permanent heterogeneity mass points.

Table 3.2: Five Year Prediction of Body Mass Status by Employment and Child Care Alternatives

Employment and child care alternatives	Exogenous OLS		Exogenous CDE		Joint DFM & CDE	
No work, no child care	0.530	(0.021)	0.417	(0.013)	0.639	(0.029)
No work, using child care	0.501	(0.082)	0.396	(0.020)	-0.794	(0.234)
Part-time, no child care	0.551	(0.022)	0.453	(0.012)	1.023	(0.297)
Part-time, using child care	0.547	(0.051)	0.467	(0.016)	0.619	(0.207)
Full-time, no child care	0.582	(0.025)	0.503	(0.012)	0.727	(0.193)
Full-time, using child care	0.618	(0.028)	0.496	(0.014)	0.884	(0.115)

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for the exogenous models and parametrically using 200 repetitions for the joint model. Model 3 is estimated using 6 permanent heterogeneity mass points.

Table 3.3: Five Year Simulation Differences of Body Mass Status by Employment and Child Care Alternatives

Employment and child care alternatives	Exogenous OLS		Exogenous CDE		Joint DFM & CDE	
Compared to no work, no child care						
No work, using child care	-0.029		-0.021		-1.433	***
	(0.084)		(0.023)		(0.232)	
Part-time, no child care	0.021		0.036	**	0.384	
	(0.028)		(0.015)		(0.300)	
Part-time, using child care	0.017		0.049	**	-0.020	
	(0.052)		(0.022)		(0.204)	
Full-time, no child care	0.052	*	0.086	***	0.087	
	(0.032)		(0.018)		(0.199)	
Full-time, using child care	0.088	**	0.079	***	0.244	**
	(0.034)		(0.020)		(0.127)	
Compared to full-time work, no child care						
No work, no child care	-0.052	*	-0.086	***	-0.087	
	(0.032)		(0.018)		(0.199)	
No work, using child care	-0.081		-0.107	***	-1.521	***
	(0.084)		(0.023)		(0.290)	
Part-time, no child care	-0.032		-0.050	***	0.297	
	(0.031)		(0.018)		(0.366)	
Part-time, using child care	-0.035		-0.036	*	-0.107	
	(0.049)		(0.020)		(0.375)	
Full-time, using child care	0.036		-0.007		0.157	
	(0.036)		(0.018)		(0.253)	

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for the exogenous models and parametrically using 200 repetitions for the joint model. Model 3 is estimated using 6 permanent heterogeneity mass points.

Table 3.4: Five Year Prediction of Body Mass Status by Employment and Child Care Alternatives: Differences by Body Mass Status in Kindergarten

	Body Mass Status in Kindergarten					
Employment and child care alternatives	Obese		Overweight		Normal	
No work, no child care	1.739	(0.056)	1.432	(0.076)	0.321	(0.030)
No work, using child care	1.136	(0.256)	-0.129	(0.497)	-1.213	(0.191)
Part-time, no child care	1.857	(0.073)	1.616	(0.146)	0.784	(0.363)
Part-time, using child care	1.776	(0.071)	1.414	(0.146)	0.292	(0.246)
Full-time, no child care	1.807	(0.063)	1.493	(0.121)	0.417	(0.233)
Full-time, using child care	1.820	(0.041)	1.561	(0.061)	0.613	(0.147)

Note: Standard errors (in parentheses) are bootstrapped parametrically using 200 repetitions.

Table 3.5: Marginal Effect of Maternal Employment and Child Care (informal or formal) Alternatives on Body Mass Status

	Exogenous				Joint	
Employment and child care alternatives	OLS		CDE		DFM & CDE	
No work, no child care			Omitted Category			
No work, use child care (informal or formal)	-0.013		-0.009		-0.675	***
	(0.035)		(0.007)		(0.181)	
Part-time, no child care	0.009		0.013	***	0.191	
	(0.011)		(0.003)		(0.158)	
Part-time, informal child care	0.043	*	0.052	**	0.041	
	(0.026)		(0.006)		(0.111)	
Part-time, formal child care	-0.058	*	-0.036	***	-0.318	*
	(0.031)		(0.008)		(0.178)	
Full-time, no child care	0.019		0.033	***	0.180	
	(0.013)		(0.003)		(0.140)	
Full-time, informal child care	0.053	***	0.050	***	0.106	*
	(0.017)		(0.004)		(0.063)	
Full-time, formal child care	0.008		0.004		-0.064	
	(0.019)		(0.004)		(0.080)	

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for the exogenous models and parametrically using 200 repetitions for the joint model. Model 3 is estimated using 6 permanent heterogeneity mass points.

Table 3.6: Five Year Prediction of Body Mass Status by Employment and Child Care (informal and formal) Alternatives

	Exogenous				Joint	
Employment and child care alternatives	OLS		CDE		DFM & CDE	
No work, no child care	0.530	(0.022)	0.417	(0.013)	0.669	(0.005)
No work, use child care (informal or formal)	0.491	(0.081)	0.395	(0.021)	-0.681	(0.546)
Part-time, no child care	0.554	(0.023)	0.451	(0.012)	1.057	(0.588)
Part-time, informal child care	0.633	(0.062)	0.551	(0.017)	0.765	(0.445)
Part-time, formal child care	0.386	(0.079)	0.321	(0.021)	0.201	(1.104)
Full-time, no child care	0.577	(0.025)	0.501	(0.013)	0.687	(0.519)
Full-time, informal child care	0.659	(0.035)	0.539	(0.014)	0.964	(0.355)
Full-time, formal child care	0.544	(0.040)	0.426	(0.016)	0.332	(0.330)

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for the exogenous models and parametrically using 200 repetitions for the joint model. Model 3 is estimated using 6 permanent heterogeneity mass points.

Table 3.7: Five Year Simulation Differences of Body Mass Status by Employment and Child Care (informal and formal) Alternatives

Employment and child care alternatives	Exogenous OLS		Exogenous CDE		Joint DFM & CDE	
Compared to no work, no child care						
No work, use child care (informal or formal)	-0.039		-0.022		-1.350	**
	(0.082)		(0.023)		(0.551)	
Part-time, no child care	0.024		0.034	**	0.388	
	(0.027)		(0.015)		(0.583)	
Part-time, informal child care	0.104		0.134	***	0.096	
	(0.065)		(0.021)		(0.450)	
Part-time, formal child care	-0.144	*	-0.096	***	-0.467	
	(0.084)		(0.024)		(1.099)	
Full-time, no child care	0.048		0.084	***	0.019	
	(0.031)		(0.018)		(0.524)	
Full-time, informal child care	0.130	***	0.122	***	0.296	
	(0.038)		(0.019)		(0.360)	
Full-time, formal child care	0.116	**	0.009		-0.336	
	(0.056)		(0.020)		(0.324)	
Compared to full-time work, no child care						
No work, no child care	-0.048		-0.084	***	-0.019	
	(0.031)		(0.018)		(0.524)	
No work, use child care (informal or formal)	-0.086		-0.106	***	-1.369	***
	(0.084)		(0.024)		(0.027)	
Part-time, no child care	-0.023		-0.050	***	0.369	
	(0.030)		(0.016)		(1.107)	
Part-time, informal child care	0.056		0.050	***	0.077	
	(0.065)		(0.018)		(0.074)	
Part-time, formal child care	-0.191	**	-0.180	***	-0.486	
	(0.083)		(0.025)		(1.623)	
Full-time, informal child care	0.082	**	0.038	**	0.277	*
	(0.040)		(0.019)		(0.164)	
Full-time, formal child care	-0.033		-0.075	***	-0.355	
	(0.048)		(0.021)		(0.849)	

Table 3.7 (continued)

Employment and child care alternatives	Exogenous OLS		Exogenous CDE		Joint DFM & CDE	
Compared to full-time work, informal child care						
No work, no child care	-0.130	***	-0.122	***	-0.296	
	(0.038)		(0.019)		(0.360)	
No work, use child care	-0.168	**	-0.144	***	-1.645	***
(informal or formal)	(0.087)		(0.025)		(0.191)	
Part-time, no child care	-0.106	***	-0.087	***	0.093	
	(0.040)		(0.018)		(0.943)	
Part-time, informal child care	-0.026		0.012		-0.199	**
	(0.067)		(0.021)		(0.090)	
Part-time, formal child care	-0.273	***	-0.218	***	-0.763	
	(0.088)		(0.026)		(1.459)	
Full-time, no child care	-0.082	**	-0.038	**	-0.277	*
	(0.040)		(0.019)		(0.164)	
Full-time, formal child care	-0.116	**	-0.113	***	-0.632	
	(0.056)		(0.021)		(0.684)	

Note: Standard errors (in parentheses) are bootstrapped non-parametrically using 200 repetitions for the exogenous models and parametrically using 200 repetitions for the joint model. Model 3 is estimated using 6 permanent heterogeneity mass points.

Table 3.8: Five Year Prediction of Body Mass Status by Employment and Child Care Alternatives: Differences by Body Mass Status in Kindergarten

Employment and child care alternatives	Body Mass Status in Kindergarten: Obese		Overweight		Normal	
No work, no child care	1.718	(0.028)	1.404	(0.083)	0.369	(0.005)
No work, use child care (informal or formal)	1.079	(0.529)	-0.113	(0.934)	-1.056	(0.474)
Part-time, no child care	1.830	(0.178)	1.611	(0.245)	0.834	(0.715)
Part-time, informal child care	1.776	(0.038)	1.499	(0.187)	0.471	(0.556)
Part-time, formal child care	1.545	(0.294)	0.882	(0.969)	-0.132	(1.252)
Full-time, no child care	1.752	(0.110)	1.401	(0.248)	0.390	(0.633)
Full-time, informal child care	1.796	(0.106)	1.524	(0.190)	0.731	(0.424)
Full-time, formal child care	1.613	(0.185)	1.127	(0.316)	-0.013	(0.354)

Note: Standard errors (in parentheses) are bootstrapped parametrically using 200 repetitions.

Appendix to Chapter 1

A.1 Fixed Effects Model

Suppose that the body mass equation can be expressed as the following

$$B_{it+1} = \beta_0 + \beta_1 B_{it} + \beta_2 D_{it} + \beta_3 B_{it} D_{it} + \beta_4 X_{it} + \beta_5 P_{it} + \mu_{2i} + e_{it}. \tag{A.1}$$

where μ_{2i} is a time-invariant unobservable that is potentially correlated with the maternal employment and child care alternatives (D_{it}). Estimation of this model by methods that fail to control for the unobservable term (e.g., ordinary least squares) will result in biased estimates of the effect of maternal employment and child care on obesity.

One possible estimation strategy for this model uses individual variation over time. Specifically, the average of each individual across time can be written as

$$\overline{B}_i = \beta_0 + \beta_1 \overline{B}_i + \beta_2 \overline{D}_i + \beta_3 \overline{B}_i \overline{D}_i + \beta_4 \overline{X}_i + \beta_5 \overline{P}_i + \mu_{2i} + \overline{e}_i \tag{A.2}$$

Subtracting this equation from equation A.2 yields

$$B_{it+1} - \overline{B}_i = \beta_1 (B_{it} - \overline{B}_i) + \beta_2 (D_{it} - \overline{D}_i) + \beta_3 (B_{it} D_{it} - \overline{B}_i \overline{D}_i) + \beta_4 (X_{it} - \overline{X}_i) + \beta_5 (P_{it} - \overline{P}_i) + (e_{it} - \overline{e}_i) \tag{A.3}$$

Differencing the two equations results in the elimination of the unobserved heterogeneity component (μ_{2i}) and the effects of maternal employment and child care on children's body mass statuses are identified by individuals' variations over time.

Unfortunately, there are several disadvantages to this fixed effect method. First, identification of the effects of interest is derived in this method from individuals' variations over time. This not only means that variables that do not vary across time are eliminated (and subsequently unidentified) but also that the coefficient estimates for those variables that do not have substantial changes over time may be imprecisely estimated.

Another problematic aspect of the fixed effect estimator is the assumption that the unobserved heterogeneity term is fixed (i.e., time invariant). If the body mass equation were rewritten as

$$B_{it+1} = \beta_0 + \beta_1 B_{it} + \beta_2 D_{it} + \beta_3 B_{it} D_{it} + \beta_4 X_{it} + \beta_5 P_{it} + \mu_{2i} + \nu_{2it} + e_{it}. \tag{A.4}$$

where ν_{2it} is a time-varying individual term that is possibly correlated with the explanatory variables, then the differencing of equation A.4 from the mean, which is

$$\begin{aligned} B_{it+1} - \overline{B}_i &= \beta_1(B_{it} - \overline{B}_i) + \beta_2(D_{it} - \overline{D}_i) + \beta_3(B_{it}D_{it} - \overline{B}_i\overline{D}_i) + \\ &\quad \beta_4(X_{it} - \overline{X}_i) + \beta_5(P_{it} - \overline{P}_i) + (\nu_{it} - \overline{\nu}_i) + (e_{it} - \overline{e}_i) \end{aligned} \tag{A.5}$$

will not eliminate the time-varying heterogeneity component. In this particular case, researchers must turn to other estimation procedures (e.g., instrumental variables estimation).

A third common problem of using the fixed effects estimation approach is the possible exacerbation of attenuation bias if the explanatory variables are measured with error. In cross sectional data, when an explanatory variable is measured with error the coefficient estimate suffers from attenuation bias. Suppose, for example that x_i^* is the correct but unobserved variable and the variable that is actually observed in the data is x_i, where

$$x_i^* = x_i + \nu \tag{A.6}$$

The correct model, $y_i = x_i^*\beta + \epsilon_i$ can be rewritten as a function of the incorrectly measured variable, or

$$\begin{aligned} y_i &= x_i\beta + (\nu\beta + \epsilon_i) \\ &= x_i\beta + \eta_i \end{aligned} \tag{A.7}$$

Taking the *plim* of the Ordinary Least Squares estimate of β, $\widehat{\beta} = (X'X)^{-1}X'Y$

$$\begin{aligned} plim\widehat{\beta} &= \beta + plim(X'X)^{-1}X'\nu \\ &= \beta + \frac{cov(x,\eta)}{var(x)} \\ &= \beta\left(\frac{\sigma_x^2}{\sigma_x^2 + \sigma_\eta^s}\right) \end{aligned} \tag{A.8}$$

where $\frac{\sigma_x^2}{\sigma_x^2+\sigma_\eta^2}$ is between 0 and 1 and therefore,

$$\widehat{\beta} < \beta \tag{A.9}$$

Measurement error in cross sectional data therefore reduces the value of $\widehat{\beta}$, resulting in what is known as attenuation bias. With fixed effects estimation however, measurement error can lead to the exacerbation of attenuation bias because the error component is often a greater proportion of the individual variation across time in comparison to measurement error that exists in cross sectional data (Angeles, Lance, and Hubbard, 2008).

The last problem with fixed effects estimation is the large loss in the degrees of freedom. In this analysis in particular, where I have 18,990 individual-time observations, estimation via fixed effects will result in a loss of 6,330 degrees of freedom.

A.2 Discrete Factor Approximation Method

Econometric Model

In the spirit of Heckman and Singer's (1984) semi-parametric estimation for duration models, the discrete factor approximation method treats the unobserved heterogeneity components as a discrete distribution. The likelihood function, conditional on the unobserved heterogeneity factors, is then integrated out over the distribution of these factors. The primary advantage of this estimation approach is that distributional assumptions about the error terms are minimized and estimation of complicated integrals is eliminated since discrete approximations are used.

To further elaborate on the details, suppose that the interest is to estimate a two equation model where the error terms are

$$\begin{aligned} \epsilon_{1t} &= \mu_1 + \nu_{1t} + e_{1t} \\ \epsilon_{2t} &= \mu_2 + \nu_{2t} + e_{2t} \end{aligned} \tag{A.10}$$

where μ_1 and μ_2 capture time-invariant individual heterogeneity and ν_{1t} and ν_{2t} are time varying individual heterogeneity components. Assuming that e_{1t} and e_{2t} are mutually independent with a probability distribution function represented by $g(\cdot)$ and $h(\cdot)$ respectively, the joint distribution of ϵ_{1t} and ϵ_{2t} conditional on μ and ν_t is written as

$$f_{\epsilon_1\epsilon_2}(\epsilon_{1t}, \epsilon_{2t}|\mu, \nu_t) = g(\epsilon_{1t} - \mu_1 - \nu_{1t})h(\epsilon_{2t} - \mu_2 - \nu_{2t}). \tag{A.11}$$

The unconditional distribution of ϵ_{1t} and ϵ_{2t} is given by

$$f_{\epsilon_1\epsilon_2}(\epsilon_{1t}, \epsilon_{2t}) = \int\int f_{\epsilon_1\epsilon_2}(\epsilon_{1t}, \epsilon_{2t}|\mu, \nu_t)f_\mu(\mu)f_\nu(\nu)\partial\mu\partial\nu \tag{A.12}$$

where $f_\mu(\mu)$ and $f_\nu(\nu)$ are probability distribution functions of μ and ν, respectively. Assuming that the distribution of μ and ν_t can be approximated with a discrete step-wise function, the integral in equation (A.2.4) can be approximated as

$$f(\epsilon_{1t}, \epsilon_{2t}) = \sum_{k=1}^{K} \pi_k \sum_{\ell=1}^{L} \psi_\ell f(\epsilon_{1t}, \epsilon_{2t} | \mu = \mu_k, \nu_t = \nu_{t\ell}) \tag{A.13}$$

where

$$\begin{aligned} \pi_k &= \Pr(\mu = \mu_k) = \Pr(\mu_1 = \mu_{1k}, \mu_2 = \mu_{2k}) \\ \psi_\ell &= \Pr(\nu_t = \nu_{t\ell}) = \Pr(\nu_{1t} = \nu_{1\ell}, \nu_{2t} = \nu_{2\ell}). \end{aligned} \tag{A.14}$$

In effect, the joint distribution can be approximated by a weighted sum over the mass points.

Computational Method

Optimization of the likelihood function, to obtain parameter estimates, is conducted using a FORTRAN program generously provided by David Guilkey. The goal of the numerical optimization process is to find parameter estimates that maximize the likelihood function. In this paper, the DFP alogorithm, from Davidson, Feltcher, and Powell, is the gradient method applied.[3]

The DFP method is a gradient method where the parameter estimates, $\widehat{\beta}$, are changed toward the direction determined by the gradient, where

$$\widehat{\beta}_{j+1} = \widehat{\beta}_j + A_j \frac{\partial \mathrm{L}(\beta)}{\partial \beta} |_{\widehat{\beta}_j} \tag{A.15}$$

where $\frac{\partial \mathrm{L}(\beta)}{\partial \beta} |_{\widehat{\beta}_j}$ is the gradient of the likelihood function evaluated at $\widehat{\beta}_j$. A_j, the weighting matrix, is

$$A_j = A_{j-1} + \frac{\delta_{j-1}\delta'_{j-1}}{\delta'_{j-1}\gamma_{j-1}} + \frac{A_{j-1}\gamma_{j-1}\gamma'_{j-1}A_{j-1}}{\gamma'_{j-1}A_{j-1}\gamma_{j-1}} \tag{A.16}$$

[3]This discussion and notation follows from Cameron and Trivedi's Microeconometrics (2005).

where

$$\begin{aligned} \delta_{j-1} &= A_{j-1} \frac{\partial \mathrm{L}(\beta)}{\partial \beta}|_{\widehat{\beta}_{j-1}} \\ \gamma_{j-1} &= \frac{\partial \mathrm{L}(\beta)}{\partial \beta}|_{\widehat{\beta}_{j}} \frac{\partial \mathrm{L}(\beta)}{\partial \beta}|_{\widehat{\beta}_{j-1}}. \end{aligned} \tag{A.17}$$

A.3 Identification

To test for the validity of the instruments, two likelihood ratio tests were conducted: a test for joint significance, which tests to see whether the variables are collectively significant in explaining the employment and child care decision variable; and a test for overidentification, which tests to see whether the variables are collectively excludable from the body mass status equation. Testing was conducted using a likelihood ration test, where the test statistic is:

$$LR = -2 \cdot [\ln\mathrm{L}(\hat{\theta}_R) - \ln\mathrm{L}(\hat{\theta}_U)]. \tag{A.18}$$

$\mathrm{L}(\hat{\theta}_R)$ is the likelihood from the unrestricted and $\mathrm{L}(\hat{\theta}_U)$ is the likelihood from the restricted specification. The null and alternative hypotheses are:

$$\begin{aligned} H_0 : \mathrm{L}(\hat{\theta}_R) &= \mathrm{L}(\hat{\theta}_U) \\ H_1 : \mathrm{L}(\hat{\theta}_R) &\neq \mathrm{L}(\hat{\theta}_U) \end{aligned} \tag{A.19}$$

To test for joint significance, the instrumental variables are excluded from the joint employment and child care decision equation. I then compare the log likelihood function of this model ($\ln \mathrm{L}(\hat{\theta}_R)$) to that of the original model ($\ln \mathrm{L}(\hat{\theta}_U)$). Failure to reject the null hypothesis would imply that the instrumental variables are jointly insignificant in explaining the employment and child care alternative equation.

Similarly, an over-identification test is conducted by including the instruments in the body mass status equation and comparing the log likelihood of this model ($\ln \mathrm{L}(\hat{\theta}_U)$) to that of the original model ($\ln \mathrm{L}(\hat{\theta}_R)$). Rejecting the null hypothesis implies that the instrumental variables are jointly significant in the body mass status outcome equation, and cannot be validly excluded from the body mass outcome equation.

Table A.1: Coefficient Estimates from Employment and Child Care Decision Equation (jointly estimated with obese outcome equation)

Variable	Not Working, using child care		Part-time, not using child care		Part-time, using child care		Full-time, not using child care		Full-time, using child care	
Current Health	0.937	(0.445)	-0.384	(0.205)	-0.080	(0.259)	-0.490	(0.234)	-0.585	(0.259)
Child characteristics										
Male	-0.146	(0.212)	0.244	(0.114)	0.169	(0.152)	0.356	(0.148)	0.311	(0.164)
Age	-1.216	(1.437)	-0.796	(0.584)	-0.060	(0.843)	-1.616	(0.716)	-2.192	(0.775)
Age squared	0.045	(0.076)	0.040	(0.030)	-0.023	(0.044)	0.067	(0.036)	0.077	(0.039)
Black	1.110	(0.440)	0.030	(0.246)	1.080	(0.300)	1.420	(0.290)	1.486	(0.317)
Hispanic	0.717	(0.338)	0.245	(0.180)	0.547	(0.242)	0.770	(0.233)	0.873	(0.262)
Siblings	-0.039	(0.085)	-0.385	(0.053)	-0.442	(0.077)	-0.609	(0.072)	-0.785	(0.082)
Mother characteristics										
Age	-0.030	(0.016)	-0.001	(0.013)	-0.050	(0.017)	-0.053	(0.015)	-0.073	(0.017)
Education										
High School	-0.593	(0.379)	0.847	(0.208)	0.934	(0.289)	0.823	(0.254)	1.079	(0.289)
Some College	-0.586	(0.363)	1.056	(0.222)	1.403	(0.302)	1.281	(0.276)	1.555	(0.309)
$\geq$ College	-0.866	(0.494)	1.519	(0.251)	1.915	(0.341)	1.956	(0.311)	2.262	(0.346)
Married	-1.623	(0.502)	0.648	(0.221)	-0.471	(0.278)	-0.468	(0.240)	-0.988	(0.263)
Prior Work	0.713	(0.423)	3.222	(0.309)	5.293	(0.400)	6.456	(0.429)	7.977	(0.488)
Father characteristics										
Age	0.052	(0.019)	0.046	(0.012)	0.033	(0.015)	0.056	(0.014)	0.039	(0.016)
Education										
High School	0.397	(0.361)	0.582	(0.216)	0.693	(0.308)	0.548	(0.266)	0.552	(0.305)
Some College	-0.384	(0.437)	0.688	(0.228)	0.470	(0.320)	0.267	(0.281)	0.234	(0.319)
$\geq$ College	-0.219	(0.463)	-0.077	(0.243)	-0.271	(0.348)	-1.362	(0.321)	-1.466	(0.362)
Time Dummy: Third Grade	0.795	(0.752)	0.903	(0.387)	0.809	(0.542)	1.863	(0.517)	2.293	(0.565)
Time Dummy: Fifth Grade	1.343	(1.193)	1.096	(0.678)	1.929	(0.948)	2.643	(0.911)	3.492	(1.006)
Food and Activity Price and Availability										
Fast Food Price	0.124	(0.135)	-0.123	(0.065)	-0.035	(0.091)	-0.057	(0.082)	-0.058	(0.091)
Restaurant Price	0.964	(0.690)	-0.671	(0.306)	-0.557	(0.426)	-0.211	(0.407)	0.011	(0.444)
# of Limited Service Restaurants	-0.887	(1.127)	-0.260	(0.516)	-0.003	(0.706)	1.051	(0.637)	0.661	(0.700)
# of Full Service Restaurants	-0.199	(0.630)	0.221	(0.343)	0.468	(0.474)	0.358	(0.443)	0.483	(0.493)

Table A.1 (continued)

Variable	Not Working, using child care		Part-time, not using child care		Part-time, using child care		Full-time, not using child care		Full-time, using child care	
# of Supermarkets	2.283	(4.258)	2.916	(1.766)	0.396	(2.437)	1.621	(2.184)	1.537	(2.402)
# of Convenience Stores	0.780	(2.072)	0.785	(0.970)	2.371	(1.320)	0.574	(1.230)	1.090	(1.355)
# of Fitness Centers	-1.619	(1.753)	0.866	(0.890)	0.618	(1.183)	-0.289	(1.120)	0.819	(1.217)
Community-level characteristics										
% in Poverty	15.435	(17.131)	-1.085	(8.568)	-4.603	(11.361)	0.280	(10.867)	5.278	(11.886)
% in Poverty Squared	-15.919	(47.155)	-14.595	(25.544)	10.927	(33.783)	-24.858	(32.732)	-19.832	(35.921)
Median Income	-0.116	(0.185)	0.075	(0.093)	0.183	(0.133)	0.003	(0.126)	0.131	(0.142)
Median Income Squared	0.003	(0.003)	-0.002	(0.002)	-0.003	(0.002)	-0.001	(0.002)	-0.003	(0.002)
% Unemployed	-21.440	(37.171)	3.558	(16.253)	45.295	(23.235)	-6.608	(20.098)	-11.770	(22.148)
% Unemployed Squared	58.624	(255.034)	-84.397	(124.612)	-396.074	(181.902)	23.093	(153.852)	0.361	(171.549)
% High School Degree	-7.387	(7.199)	6.930	(2.980)	7.929	(4.093)	6.240	(3.660)	3.132	(4.038)
% College Degree	-1.166	(4.464)	1.634	(1.900)	0.729	(2.663)	-0.069	(2.416)	-0.079	(2.676)
TANF Benefits	0.010	(0.018)	0.004	(0.008)	-0.004	(0.011)	-0.006	(0.010)	0.001	(0.011)
TANF Benefits Squared	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
Mandatory Job Search	-0.260	(0.334)	0.254	(0.128)	0.480	(0.183)	0.511	(0.161)	0.625	(0.179)
Mean Wage	1.244	(3.345)	-1.072	(1.485)	1.235	(2.101)	1.709	(1.864)	2.412	(2.051)
Mean Wage Squared	-0.188	(0.375)	0.127	(0.163)	-0.129	(0.231)	-0.218	(0.206)	-0.297	(0.226)
# Centers	-0.308	(1.181)	0.466	(0.595)	1.401	(0.819)	0.198	(0.771)	0.436	(0.854)
# Family Centers	-0.461	(0.245)	0.007	(0.105)	-0.071	(0.149)	0.201	(0.139)	0.147	(0.152)
Center License	0.104	(0.351)	-0.003	(0.167)	0.022	(0.233)	-0.009	(0.233)	0.043	(0.256)
Family License	0.255	(0.295)	-0.481	(0.155)	-0.275	(0.211)	-0.235	(0.203)	-0.125	(0.225)
Groups License	-0.080	(0.354)	0.338	(0.175)	0.408	(0.240)	0.199	(0.225)	0.403	(0.249)
Constant	-58.740	(8.145)	-8.556	(5.261)	-36.304	(5.844)	-15.682	(6.594)	39.442	(3.539)
Likelihood ratio statistic for test of joint significance			149.397							
Likelihood ratio statistic for test of over-identification			31.076							

Notes: Standard errors in parentheses.

Table A.2: Coefficient Estimates from Employment and Child Care Decision Equation (jointly estimated with overweight outcome equation)

Variable	Not Working, using child care		Part-time, not using child care		Part-time, using child care		Full-time, not using child care		Full-time, using child care	
Current Health	0.205	(0.418)	0.114	(0.127)	0.494	(0.211)	0.050	(0.169)	-0.002	(0.220)
Child characteristics										
Male	-0.285	(0.270)	0.027	(0.102)	-0.092	(0.141)	0.076	(0.129)	-0.011	(0.148)
Age	-2.058	(1.720)	-0.643	(0.574)	0.046	(0.827)	-1.346	(0.729)	-1.924	(0.809)
Age squared	0.101	(0.091)	0.041	(0.030)	-0.017	(0.044)	0.068	(0.037)	0.079	(0.042)
Black	1.536	(0.532)	-0.075	(0.216)	1.074	(0.273)	1.294	(0.239)	1.388	(0.268)
Hispanic	1.010	(0.461)	-0.062	(0.166)	0.264	(0.228)	0.427	(0.204)	0.501	(0.237)
Siblings	-0.237	(0.112)	-0.321	(0.046)	-0.397	(0.068)	-0.489	(0.063)	-0.661	(0.074)
Mother characteristics										
Age	-0.055	(0.018)	0.001	(0.012)	-0.056	(0.016)	-0.048	(0.014)	-0.071	(0.016)
Education										
High School	-0.261	(0.322)	0.610	(0.195)	0.712	(0.277)	0.626	(0.235)	0.820	(0.275)
Some College	-0.574	(0.396)	0.835	(0.209)	1.198	(0.290)	1.165	(0.251)	1.407	(0.290)
$\geq$ College	-0.915	(0.611)	1.138	(0.235)	1.476	(0.327)	1.576	(0.291)	1.816	(0.334)
Married	-1.956	(0.470)	0.581	(0.217)	-0.546	(0.273)	-0.377	(0.233)	-0.943	(0.261)
Prior Work	-0.530	(0.389)	4.221	(0.275)	7.087	(0.391)	8.465	(0.508)	10.661	(0.625)
Father characteristics										
Age	0.060	(0.020)	0.032	(0.011)	0.019	(0.014)	0.024	(0.013)	0.003	(0.015)
Education										
High School	0.514	(0.430)	0.475	(0.207)	0.622	(0.296)	0.311	(0.244)	0.289	(0.288)
Some College	-0.417	(0.541)	0.479	(0.213)	0.241	(0.306)	-0.065	(0.257)	-0.165	(0.301)
$\geq$ College	-0.614	(0.640)	-0.055	(0.229)	-0.151	(0.327)	-1.271	(0.285)	-1.439	(0.334)
Time Dummy: Third Grade	1.071	(0.933)	0.490	(0.349)	0.363	(0.493)	1.233	(0.459)	1.604	(0.515)
Time Dummy: Fifth Grade	1.066	(1.460)	0.359	(0.603)	1.069	(0.853)	1.505	(0.782)	2.243	(0.887)
Food and Activity Price and Availability										
Fast Food Price	0.051	(0.187)	-0.105	(0.060)	0.004	(0.086)	-0.025	(0.075)	-0.014	(0.086)
Restaurant Price	0.824	(0.924)	-0.468	(0.279)	-0.356	(0.397)	-0.014	(0.362)	0.181	(0.412)
# of Limited Service Restaurants	-2.079	(1.587)	-0.135	(0.503)	0.051	(0.678)	1.008	(0.596)	0.688	(0.664)
# of Full Service Restaurants	-0.510	(0.834)	0.002	(0.325)	0.038	(0.448)	-0.047	(0.395)	0.021	(0.453)

Table A.2 (continued)

Variable	Not Working, using child care		Part-time, not using child care		Part-time, using child care		Full-time, not using child care		Full-time, using child care	
# of Supermarkets	4.628	(5.280)	1.927	(1.709)	-0.471	(2.398)	1.438	(2.127)	1.458	(2.401)
# of Convenience Stores	2.331	(2.765)	0.218	(0.893)	1.563	(1.253)	-0.112	(1.109)	0.263	(1.272)
# of Fitness Centers	-1.913	(2.484)	0.617	(0.827)	0.306	(1.120)	-1.123	(1.025)	-0.117	(1.154)
Community-level characteristics										
% in Poverty	22.181	(22.129)	-5.320	(7.637)	-5.720	(10.706)	-0.563	(9.688)	4.882	(11.092)
% in Poverty Squared	-35.974	(56.929)	0.954	(22.461)	17.630	(31.929)	-17.003	(28.971)	-9.518	(33.344)
Median Income	-0.203	(0.240)	0.035	(0.083)	0.112	(0.126)	-0.110	(0.111)	0.031	(0.128)
Median Income Squared	0.004	(0.004)	-0.001	(0.001)	-0.002	(0.002)	0.001	(0.002)	-0.001	(0.002)
% Unemployed	-20.296	(42.161)	10.895	(16.426)	46.995	(23.926)	2.449	(20.263)	-8.297	(22.817)
% Unemployed Squared	-36.974	(278.027)	-122.843	(129.600)	-397.672	(191.749)	-45.721	(157.734)	-26.282	(178.043)
% High School Degree	-6.025	(8.462)	6.380	(2.770)	6.313	(3.880)	5.937	(3.475)	2.577	(3.956)
% College Degree	6.506	(6.926)	0.834	(1.788)	0.030	(2.539)	-1.425	(2.249)	-1.492	(2.576)
TANF Benefits	-0.005	(0.024)	-0.001	(0.007)	-0.005	(0.010)	-0.013	(0.009)	-0.006	(0.011)
TANF Benefits Squared	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
Mandatory Job Search	-0.350	(0.429)	0.187	(0.122)	0.448	(0.176)	0.431	(0.152)	0.517	(0.171)
Mean Wage	3.977	(4.540)	-0.678	(1.392)	1.701	(2.044)	3.086	(1.819)	3.935	(2.071)
Mean Wage Squared	-0.562	(0.508)	0.094	(0.154)	-0.174	(0.226)	-0.359	(0.202)	-0.456	(0.230)
# Centers	0.866	(1.671)	1.056	(0.516)	2.072	(0.724)	0.664	(0.642)	0.794	(0.741)
# Family Centers	-0.608	(0.320)	-0.014	(0.091)	-0.099	(0.135)	0.165	(0.113)	0.089	(0.131)
Center License	-0.351	(0.462)	-0.028	(0.144)	-0.026	(0.207)	-0.084	(0.190)	-0.037	(0.216)
Family License	0.101	(0.360)	-0.632	(0.133)	-0.468	(0.187)	-0.431	(0.170)	-0.341	(0.195)
Groups License	0.228	(0.464)	0.405	(0.158)	0.543	(0.222)	0.352	(0.197)	0.585	(0.227)
Constant	-20.174	(10.330)	-30.153	(19.650)	-31.824	(7.376)	-25.692	(6.513)	-43.289	(4.794)
Likelihood ratio statistic for test of joint significance			205.028							
Likelihood ratio statistic for test of over-identification			32.386							

Notes: Standard errors in parentheses.

Table A.3: Coefficient Estimates from Employment and Child Care Decision Equation (jointly estimated with BMI outcome equation)

Variable	Not Working, using child care		Part-time, not using child care		Part-time, using child care		Full-time, not using child care		Full-time, using child care	
Current Health	0.002	-(0.507)	-0.002	(0.002)	0.002	(0.003)	-0.002	(0.003)	0.001	(0.003)
Child characteristics										
Male	0.009	(0.137)	0.078	(0.121)	0.043	(0.139)	0.236	(0.163)	0.216	(0.150)
Age	-0.804	(1.001)	-0.693	(0.733)	0.126	(0.862)	-1.193	(0.914)	-1.373	(0.835)
Age squared	0.035	(0.054)	0.046	(0.038)	-0.017	(0.045)	0.069	(0.047)	0.056	(0.043)
Black	0.871	(0.240)	0.178	(0.251)	0.818	(0.278)	1.423	(0.325)	1.093	(0.283)
Hispanic	0.561	(0.199)	-0.121	(0.208)	-0.058	(0.234)	0.275	(0.270)	0.175	(0.245)
Siblings	-0.112	(0.062)	-0.320	(0.054)	-0.327	(0.063)	-0.427	(0.071)	-0.531	(0.067)
Mother characteristics										
Age	-0.032	(0.012)	-0.018	(0.013)	-0.063	(0.015)	-0.062	(0.017)	-0.078	(0.014)
Education										
High School	-0.175	(0.212)	1.024	(0.241)	0.919	(0.277)	0.997	(0.317)	1.150	(0.286)
Some College	-0.204	(0.233)	1.102	(0.249)	1.303	(0.287)	1.378	(0.331)	1.561	(0.303)
$\geq$ College	-0.392	(0.293)	1.434	(0.285)	1.513	(0.329)	1.906	(0.381)	1.968	(0.348)
Married	-1.045	(0.231)	0.385	(0.238)	-0.532	(0.266)	-0.603	(0.299)	-1.047	(0.258)
Prior Work	1.517	(0.551)	6.722	(0.826)	7.425	(0.813)	8.952	(0.811)	8.811	(0.789)
Father characteristics										
Age	0.040	(0.011)	0.026	(0.013)	0.013	(0.014)	0.035	(0.017)	0.014	(0.015)
Education										
High School	0.212	(0.247)	0.674	(0.257)	0.770	(0.297)	0.634	(0.328)	0.626	(0.302)
Some College	-0.163	(0.276)	0.505	(0.264)	0.320	(0.306)	0.113	(0.342)	0.106	(0.316)
$\geq$ College	-0.233	(0.296)	-0.088	(0.276)	-0.141	(0.321)	-1.158	(0.362)	-1.088	(0.335)
Time Dummy: Third Grade	0.464	(0.505)	0.763	(0.429)	0.525	(0.485)	1.462	(0.557)	1.593	(0.508)
Time Dummy: Fifth Grade	0.600	(0.807)	0.650	(0.703)	1.226	(0.808)	1.546	(0.936)	2.175	(0.862)
Food and Activity Price and Availability										
Fast Food Price	0.080	(0.091)	-0.093	(0.071)	0.024	(0.085)	-0.060	(0.095)	-0.022	(0.089)
Restaurant Price	0.709	(0.453)	-0.496	(0.321)	-0.345	(0.382)	-0.059	(0.439)	0.150	(0.406)
# of Limited Service Restaurants	-0.502	(0.773)	-0.551	(0.562)	-0.294	(0.664)	0.590	(0.715)	0.143	(0.660)
# of Full Service Restaurants	-0.051	(0.432)	0.367	(0.391)	0.503	(0.445)	0.272	(0.491)	0.475	(0.444)

Table A.3 (continued)

Variable	Not Working, using child care		Part-time, not using child care		Part-time, using child care		Full-time, not using child care		Full-time, using child care	
# of Supermarkets	1.611	(2.702)	2.809	(2.028)	0.295	(2.358)	1.286	(2.607)	0.852	(2.385)
# of Convenience Stores	1.074	(1.403)	-0.551	(1.070)	0.640	(1.239)	-1.368	(1.378)	-1.033	(1.275)
# of Fitness Centers	-0.400	(1.131)	1.241	(0.979)	1.122	(1.107)	0.175	(1.269)	1.017	(1.118)
Community-level characteristics										
% in Poverty	10.044	(11.977)	-12.856	(9.254)	-11.349	(10.652)	-7.733	(12.234)	1.527	(11.217)
% in Poverty Squared	-12.277	(33.176)	27.783	(28.089)	40.199	(32.086)	5.356	(37.136)	5.652	(33.572)
Median Income	-0.069	(0.125)	0.146	(0.102)	0.232	(0.117)	0.075	(0.131)	0.208	(0.123)
Median Income Squared	0.002	(0.002)	-0.003	(0.002)	-0.004	(0.002)	-0.003	(0.002)	-0.004	(0.002)
% Unemployed	-7.503	(22.623)	3.923	(20.412)	44.056	(23.632)	1.349	(25.336)	-7.106	(23.117)
% Unemployed Squared	-0.043	(157.312)	-86.816	(158.366)	-370.627	(184.180)	-60.391	(196.615)	-42.289	(179.278)
% High School Degree	-2.871	(4.304)	7.484	(3.316)	7.482	(3.858)	7.649	(4.315)	3.619	(3.975)
% College Degree	-2.616	(2.996)	0.787	(2.073)	-1.421	(2.454)	-0.274	(2.770)	-2.109	(2.561)
TANF Benefits	0.004	(0.012)	-0.006	(0.009)	-0.006	(0.011)	-0.017	(0.012)	-0.005	(0.011)
TANF Benefits Squared	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)	0.001	(0.001)
Mandatory Job Search	-0.200	(0.226)	0.294	(0.151)	0.413	(0.179)	0.535	(0.197)	0.503	(0.182)
Mean Wage	1.032	(2.259)	-1.821	(1.742)	0.790	(2.029)	0.243	(2.220)	2.130	(2.029)
Mean Wage Squared	-0.138	(0.252)	0.226	(0.194)	-0.060	(0.225)	-0.030	(0.248)	-0.235	(0.226)
# Centers	-0.118	(0.810)	0.348	(0.592)	1.203	(0.692)	0.541	(0.786)	1.109	(0.734)
# Family Centers	-0.264	(0.153)	-0.020	(0.112)	-0.119	(0.133)	0.123	(0.146)	-0.006	(0.136)
Center License	0.008	(0.236)	0.048	(0.172)	0.011	(0.201)	-0.029	(0.231)	-0.035	(0.214)
Family License	0.134	(0.195)	-0.555	(0.167)	-0.286	(0.191)	-0.399	(0.221)	-0.284	(0.205)
Groups License	-0.059	(0.241)	0.264	(0.196)	0.324	(0.226)	0.114	(0.261)	0.289	(0.243)
Constant	-2.176	(8.000)	-9.202	(6.102)	-21.472	(7.076)	-13.748	(7.787)	-14.221	(7.147)

Likelihood ratio statistic for test of joint significance	141.570
Likelihood ratio statistic for test of over-identification	22.686

Notes: Standard errors in parentheses.

Table A.4: Coefficients for Initial Body Mass Status

	Body Mass Outcome								
Variable	Obese			Overweight			BMI-Percentile		
Child characteristics									
Male	0.19	(0.09)	**	0.16	(0.07)	**	1.07	(0.70)	
Age	0.26	(0.16)	*	0.47	(0.13)	***	4.21	(1.41)	***
Black	0.42	(0.13)	***	0.46	(0.11)	***	4.77	(1.16)	***
Hispanic	0.18	(0.12)		0.08	(0.09)		-0.12	(1.02)	
Siblings	-0.19	(0.04)	***	-0.15	(0.03)	***	-0.78	(0.34)	**
Birth Weight	0.43	(0.08)	***	0.47	(0.06)	***	7.58	(0.59)	***
Mother characteristics									
Married	-0.23	(0.16)		-0.13	(0.13)		-2.24	(1.49)	
Age	0.01	(0.01)		0.01	(0.01)		0.06	(0.08)	
Education									
High School	-0.01	(0.16)		0.01	(0.14)		-1.21	(1.45)	
Some College	-0.07	(0.17)		0.01	(0.14)		-2.19	(1.49)	*
$\geq$ College	-0.46	(0.20)	**	-0.04	(0.15)		-2.53	(1.65)	
Father characteristics									
Age	0.01	(0.01)		0.01	(0.01)		-0.14	(0.08)	
Education									
High School	-0.28	(0.17)	*	-0.25	(0.14)	**	-1.59	(1.51)	***
Some College	-0.12	(0.18)		-0.17	(0.14)		-1.05	(1.58)	
$\geq$ College	-0.71	(0.20)	***	-0.55	(0.15)	***	-4.59	(1.67)	***

Table A.4 (continued)

	Body Mass Outcome								
Variable	Obese			Overweight			BMI-Percentile		
Food and Activity Price and Availability									
Fast Food Price	0.01	(0.07)		0.03	(0.05)		0.15	(0.55)	
Restaurant Price	0.05	(0.35)		-0.40	(0.26)		-8.33	(2.81)	
# of Limited Service Restaurants	1.37	(0.49)	***	0.67	(0.38)	*	4.18	(3.90)	***
# of Full Service Restaurants	-0.48	(0.29)	*	-0.32	(0.22)		-3.87	(2.39)	**
# of Supermarkets	-2.13	(1.81)		-1.67	(1.37)		-0.42	(14.61)	***
# of Convenience Stores	-0.06	(0.83)		1.99	(0.63)	***	20.23	(6.90)	**
# of Fitness Centers	1.51	(0.71)	**	0.94	(0.54)	*	14.08	(6.03)	
Community-level characteristics									
% in Poverty	-1.42	(6.87)		-3.94	(5.19)		-82.54	(25.73)	
% in Poverty Squared	-17.11	(20.14)		3.14	(14.73)		103.75	(51.12)	
Median Income	-0.19	(0.07)	***	-0.09	(0.06)		-0.38	(0.61)	
Median Income Squared	0.01	(0.01)	***	0.01	(0.01)		0.01	(0.01)	
% Unemployed	-0.11	(3.09)		-0.04	(2.46)		22.62	(25.95)	**
% High School Degree	-0.80	(1.95)		-0.64	(1.50)		-17.09	(15.45)	***
% College Degree	0.41	(1.65)		-0.41	(1.24)		8.37	(13.05)	
# Centers	-0.28	(0.62)		0.03	(0.47)		-2.25	(5.05)	
Mean Wage	0.41	(0.13)	***	0.30	(0.10)	***	2.32	(1.03)	
Constant	-2.18	(2.40)		-79.33	(1.59)	***	82.26	(18.83)	

Note: Standard errors in parentheses. *** indicates significance at 1%, ** 5%, and * 10%.

A.4 Variable Construction

This section provides a detailed explanation of how the variables used in the analysis were constructed.

Body Mass Index

Body Mass Index (BMI) is defined as the ratio of an individual's weight in kilograms to height in meters squared. The Centers for Disease Control and Prevention (CDC) defines critical BMI ranges to be the following:

Body Mass Status	Body Mass Index (BMI)
Underweight	Less than 18.5
Healthy Weight	18.5 to 24.9
Overweight	25.0 to 29.9
Obese	30.0 to 34.9
Morbidly obese	Greater than 35.0

However, for children and adolescents (i.e., individuals under the age of nineteen) BMI alone cannot be used as a measure of body mass status, because it does not control for changes in a child's body composition by age and sex. Instead, the CDC has developed growth charts that allow children's BMIs to be plotted against the BMI for a specific age group and sex. For children, critical BMI-for-age-and-sex-percentile ranges are defined as the following:

Body Mass Status	BMI-for-age-and-sex-percentile
Underweight	Less than 5^{th} percentile
Healthy Weight	5^{th} to 84.9^{th} percentile
Overweight	85^{th} to 94.9^{th} percentile
Obese	Greater than 95^{th} percentile

The 2000 CDC Growth Charts (see Figure D1) are used to determine BMI-percentile-for-age-and-sex. These growth charts were developed using nationally representative survey data from NHANES I (1971-75), NHANES II (1976-80), and NHANES III (1988-94). Using measurements of height (C*HEIGHT, where *=1,...,6) and weight (C*WEIGHT, where *=1,...,6) available in every wave of the ECLS-K,a child's BMI is estimated and then compared against the CDC BMI-for-age-and-sex-percentile growth charts. The BMI z-score, or deviations of the BMI-for-age-and-sex from the mean of the reference population, was determined using the STATA command: zanthro. Z-scores were then converted to BMI-percentiles assuming a standard normal distribution. Using the cutoffs described above, a child is recorded as being overweight if his/her BMI-for-age-and-sex-percentile exceeds the 85^{th} percentile and obese if BMI exceeds the 95^{th} percentile. Unlike many other surveys where height and weight are self-reported, those reported in the ECLS-K are those evaluated by the in-home surveyor at the time of interview (thereby reducing the possibility of measurement error).

Employment

The data provides employment hours for two households members (usually the mother and father). The survey also provides the roster number of the two household members (P*EMQHH1 and P*EMQHH2, *=1,..,6) and the roster number of the mother (MOMID). The mother's number of hours of employment was defined by P*EMQHH1 if the mother's ID equaled the roster number of household member number 1, and her employment hours were defined by P*EMQHH2 if her ID equaled the roster number of household member number 2.

Employment hours were discretized into three categories: no employment, if weekly employment hours were less than or equal to five; part-time, if weekly employment hours were greater than five, but less than or equal to 35; and full-time, if weekly employment hours exceeded 35. The 35 hours/week cutoff is arbitrary, but is commonly used as the cutoff point between part- and full-time work, (for example by the Bureau of Labor Statistics).

Child Care

Child care hours were constructed for regular child care (defined as care received more than once per week) and non-regular child care. I also divide regular/non-regular child care into three types of care: relative, defined as care received from family members; non-relative, defined as care received from non family members such as a baby sitter; and center based care, defined as care received in a child care center or facility. If the child used any particular type of child care regularly, then the number of hours of receipt of that type of care was coded as the number of hours given. A more detailed explanation of how child care was coded is available in the ECLS-K User's Manual.

Exogenous Child-level Characteristics

Age

The child's age for waves 1 and 2 were estimated using their date of birth and the interview assessment dates. For the other waves, the variable R*AGE (*= 3,4,5,6) was used.

Gender

The child's gender variable, xmale, was constructed from variables GENDER, R5GENDER, and R6GENDER which equals 1 if GENDER, R5GENDER, or R6GENDER was equal to 1. Otherwise, the xmale variable was set to 0.

Race

The child's race variable was used variables RACE, R5RACE, R6RACE to construct indicators for xblack and xhisp. Children who were Hispanic, with no race indicated were also labeled as being Hispanic.

Number of siblings

Number of siblings was coded from variable P*NUMSIB (*=1,2,4,5,6). If the number of siblings in a wave was missing and the number of siblings preceding and following that wave were equal, then the missing value was coded as the number of siblings in two (proceeding and following) waves.

Birth weight

The child's birth weight variable is reported under P*WEIGHP and P*WEIGHTO (* = 1,2,3, or 4) which is the birth weight in pounds and ounces, respectively. Values were labeled as missing if either pounds or ounces were missing. Values were then converted into kilograms for ease.

Exogenous Family-level Characteristics

Mother and father's age

The mother and father's age in years was determined from the variable P*HMAGE and P*HDAGE, where *=1, 2, ...6, respectively. It should be noted that this is not necessarily the biological mother of the child, but rather the age of the mother with whom the child resides.

Mother and father's education

Four education dummies, less than high school, high school only, some college, and college or more, were constructed from variable W*MOMED and W*DADED (*=K,1,3,5).

Household income

Four household income dummies, which corresponds to income between $0-$25,000, $25,000-$50,000, $50,000-$75,000, and more then $75,000 were constructed using variable W*INCOME (*=1,2,..6).

Marital status

Lastly, the mother's martial status dummy was set to 1 if variable P*CURMAR (*=2,3..,6) was coded as being married. If the mother's marital status in a wave was missing, and her marital status in the waves preceding and following that wave were equal, then her marital status was coded to be equal to those two waves.

Exogenous Contextual Variables

I also merge several variables with data from the ECLS-K using the child's zip code.

Availability of establishments

The number of establishments available in the county is available from the U.S. Census's County Business Patterns (CBP) data and can be downloaded from http:// www.census.gov/ epcd/ cbp/ download/ cbpdownload.html. Data from the CBP include the number of establishments in a particular area (i.e. zip code, county, or State). Establishments are classified under the North American Industry Classification System (NAICS) and Industries are classified using a six digit numbering system. After obtaining the number of establishments of industries of interest, I estimate the total number of establishments per 1,000 people in a give geographical area.

I classify all establishments with the North American Industry Classification System (NAICS) number equal to 445110 as supermarkets and grocery stores (excluding conveniences stores). The Census defines NAICS number 44510 as the following: "This industry comprises establishments generally known as supermarkets and grocery stores primarily engaged in retailing a general line of food, such as canned and frozen foods; fresh fruits and vegetables; and fresh and prepared meats, fish, and poultry. Included in this industry are delicatessen-type establishments primarily engaged in retailing a general line of food."All establishments with the NAICS number 445120 are labeled convenience stores. The NAICS defines these establishments as the following: "This industry comprises establishments known as convenience stores or food marts (except those with fuel pumps) primarily engaged in retailing a limited line of goods that generally includes milk, bread, soda, and snacks."

I define NAICS number 713940 as Fitness and Recreational Sports Centers. The NAICS defines these establishments as the following: "This industry comprises establishments primarily engaged in operating fitness and recreational sports facilities featuring exercise and other active physical fitness conditioning or recreational sports activities, such as swimming, skating, or racquet sports."Establishments with NAICS number equal to 624410 are defined as Child Day Care Services establishments. The NAICS defines these establishments as the following: "This industry comprises establishments primarily engaged in providing day care of infants or children. These establishments generally care for preschool children, but may care for older children when they are not in school and may also offer prekindergarten educational programs."

NAICS number 722110 is the the industry coding for full-service Restaurants. The NAICS defines these establishments as the following: "This U.S. industry comprises establishments primarily engaged in providing food services to patrons who order and are served while seated (i.e. waiter/waitress service) and pay after eating. These establishments may provide this type of food services to patrons in combination with selling alcoholic beverages, providing takeout services, or presenting live nontheatrical entertainment."NAICS number 722211 is the industry coding for Limited-Service Restaurants. The NAICS defines these establishments as the following: "This U.S. industry comprises establishments primarily engaged in providing food services (except snack and nonalcoholic beverage bars)where patrons generally order or select items and pay before eating.Food and drink may be consumed on premises, taken out, or delivered to customers' location. Some establishments in this industry may provide these food services in combination with selling alcoholic beverages."

Price of fast food and restaurant meals

Price of Fast Food and Restaurant Meals in a state are determined by using data available from the U.S. Census of Retail Trade Miscellaneous Subjects 1977, 1982, 1987, 1992, 1997, 2002. Definition of Fast Food is the same as Limited Service Eating Places.and the definition of Restaurant Meals is the same as Full Service Restaurants. The prices ranged from less than $2.00, $2.00-$4.99,... up until greater than $30.00. The midpoint of prices was taken for values that had both a max and a min, otherwise for less than $2.00, took $1.50 and more than $30.00 took $45.00 as the price. To get average price, take the weighted average of prices by the number of establishments. The prices are all real prices, deflated by the CPI to 1982-1984 base dollars. Years that were missing were imputed by extrapolating and and interpolating using the STATA ipolate command. I would also like to thank Dr. Inas Rashad who graciously provided information on how to collect this data. Data for 1997 and 2002 are available online at: http://www.census.gov/econ/census02/guide/SUBSUMM.HTM.

Labor market variables

Using Occupation Employment Statistics from the Bureau of Labor and Statistics, I also get median and mean child care workers' wages and the total number of child care workers in a given Metropolitan Statistical Area (MSA). This data can be downloaded from: http://www.bls.gov/oes The wages are deflated to 1982-1984 dollars using the CPI. Metropolitan Statistical Areas are defined by the Office of Management and Budget and is a contiguous area of high population density. Thus, several zip codes can be a part of an MSA. However, areas with low population density are often not categorized in any MSA, resulting in zip codes without any information on child care workers' wages. In such cases, I use the mean and median wages of the State. It should be noted, that the number of child care workers in a given area is standardized by taking the number of workers per 1,000 people in a particular geographical area (i.e. MSA or State).

County level unemployment rates and median income are obtained from BLS and Census, respectively. Median income is deflated to 1982-1984 dollars. Unemployment rates can be downloaded from: http://www.bls.gov/lau/home.htm and median income from: http://www.census.gov/hhes/www/saipe/tables.html. Lastly, State level education data is obtained from the Census. The data includes the percentage of individuals in a State over 25 years of age that have completed high school and have completed college. This data can be downloaded from: http://www.census.gov/population/www/socdemo/educ-attn.html.

Child care variables

Child care regulation information was obtained from the Family Child Care Licensing Study and Child Care Center Licensing Study published by The Children's Foundation (currently known as the National Child Care Information and Technical Assistance Center). Family Child Care Centers are defined as child care taking place in one's residence, whereas child care centers are those in non-residential facilities. Licensing of these child care centers differ by State as well as the frequency for renewal of licenses. Licenses usually require that facilities maintain a specific standard of care. The number of child care centers and family child care centers are per 1,000 individuals residing in a given State.

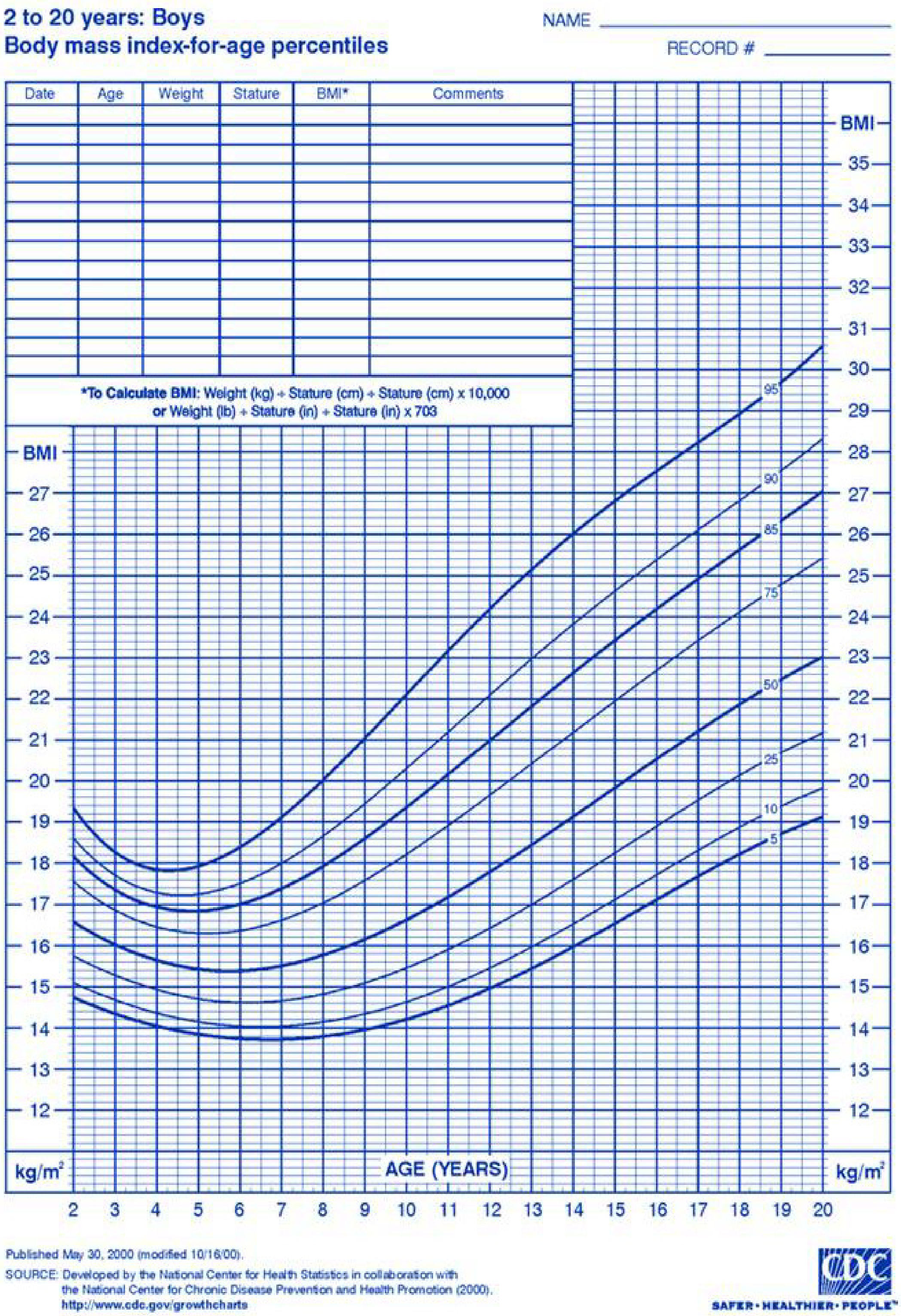


Figure A.1: CDC BMI Growth Chart (Male)

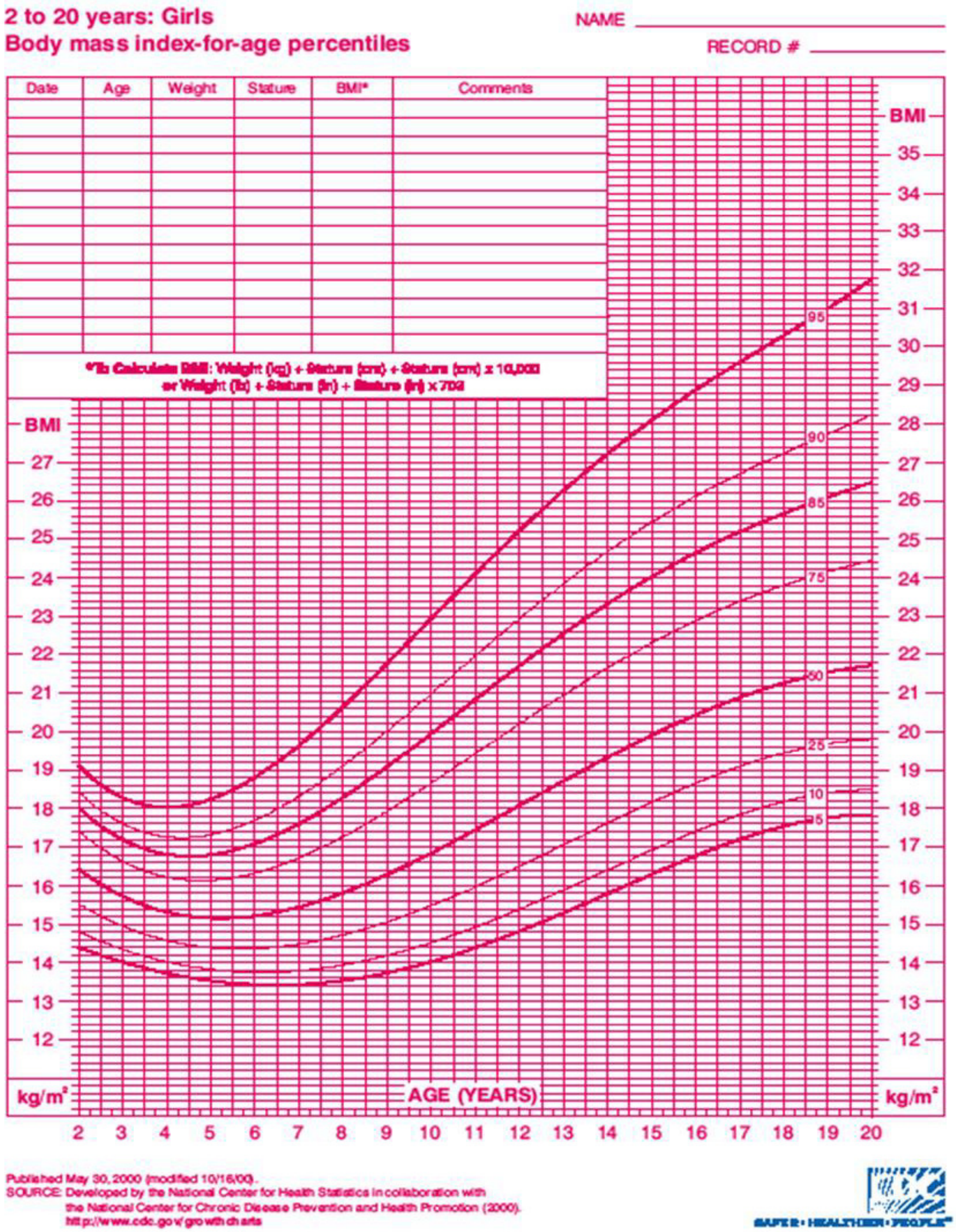


Figure A.2: CDC BMI Growth Chart (Female)

A.5 Descriptive Statistics

Table A.5 presents summary statistics of body mass status by grade, gender, and race. The first three rows are percentages of overweight and obese children, and the mean BMI-percentile-for-sex-and-age for the overall sample (i.e, 22,329 individual-year observations), by gender, and by race. The summary statistics show that boys are more likely to be obese or overweight and have higher BMIs than girls. Furthermore, blacks and Hispanics have similar body mass status averages compared to those individuals who are neither black nor Hispanic. There is significant variation in body mass status over time. Body mass statuses increase quite dramatically from the first to the fifth grades for the overall sample, as well as by gender and by race.

In Table A.6, I present summary statistics for the number of hours spent in alternative types of child care: informal with and without a relative and formal, by employment categories. Children with mothers that do not work, but use child care are more likely to participate in informal care with a relative than children whose mothers work full-time. Children whose mothers work full-time are slightly more likely to participate in formal child care than those whose mothers work either part-time or do not work at all.

In Table A.7, I compare simple descriptive statistics by whether or not the child used child care (for children whose mothers were employed full-time). I find that mothers who used child care while working full-time were significantly less likely to be married, more likely to be in the lowest income group, more likely to have some college education, but less likely to have a college degree or more than a college degree.

In Table A.8, I present descriptive statistics of body mass status by employment and child care alternatives, and by marital status. I find that children's risk of being obese or overweight is higher when the mother is single, than when she is married. Lastly, in Table A.9 I present descriptive statistics of body mass status by employment and child care alternatives, and by income. Children are less likely to be obese or overweight when the total household income is in the highest income category. In addition, the risk of being obese and overweight declines when moving to higher income categories.

Table A.5: Descriptive Statistics of Body Mass Status by Whole Sample, Gender, and Race

		Gender		Race		
Variable	Full Sample	Female	Male	Black	Hispanic	Other
Overall						
Obese (%)	16.22	14.22	18.20	21.30	22.23	14.24
Overweight (%)	31.64	29.44	33.81	37.97	40.18	28.93
BMI-percentile	63.10	63.10	63.10	63.10	63.10	63.10
First Grade						
Obese (%)	12.37	11.12	13.60	16.90	16.98	10.77
Overweight (%)	25.43	24.15	26.70	32.39	32.55	22.97
BMI-percentile	63.10	63.10	63.10	63.10	63.10	63.10
Third Grade						
Obese (%)	16.82	15.07	18.55	20.42	23.45	14.88
Overweight (%)	32.80	30.33	35.22	37.15	41.93	30.19
BMI-percentile	63.10	63.10	63.10	63.10	63.10	63.10
Fifth Grade						
Obese (%)	19.48	16.47	22.44	26.58	26.27	17.07
Overweight (%)	36.70	33.83	39.52	44.37	46.06	33.64
BMI-percentile	63.10	63.10	63.10	63.10	63.10	63.10

Table A.6: Descriptive Statistics of Hours per Week Spent in Alternative Types of Child Care, by Employment Status

		Type of care		
Employment alternatives	Total	Relative	Non-relative	Formal
No work	13.7	8.3	1.5	3.9
Part-time	11.8	6.2	2.0	3.6
Full-time	13.2	6.7	2.2	4.3

Table A.7: Comparison of Descriptive Statistics for Individuals Using and Not Using Child Care while Employed Full Time

Variable	Employed full-time and: Not using child care	Employed full-time and: Using child care	Difference	
Married	0.802	0.664	0.138	***
	(0.006)	(0.007)	(0.010)	
Mother characteristics				
Age	38.466	37.367	1.098	
	(0.094)	(0.098)	(0.136)	
Household Income				
$0-$25,000	0.154	0.169	-0.016	**
	(0.006)	(0.006)	(0.008)	
$25,000-$50,000	0.316	0.302	0.014	
	(0.007)	(0.007)	(0.010)	
$50,000-$75,000	0.216	0.214	0.002	
	(0.006)	(0.006)	(0.009)	
>$75,000	0.314	0.315	-0.001	
	(0.007)	(0.007)	(0.010)	
Occupation prestige	45.185	45.089	0.096	
	(0.183)	(0.170)	(0.251)	
Number of jobs	1.104	1.074	0.030	***
	(0.005)	(0.004)	(0.007)	
Employment hours (weekly)	43.358	43.113	0.245	*
	(0.106)	(0.101)	(0.146)	
Education				
< High School	0.077	0.060	0.017	***
	(0.004)	(0.004)	(0.006)	
High School	0.242	0.257	-0.015	*
	(0.007)	(0.007)	(0.009)	
Some College	0.357	0.374	-0.017	*
	(0.007)	(0.008)	(0.011)	
≥College	0.325	0.309	0.016	
	(0.007)	(0.007)	(0.010)	
Father characteristics				
Age	41.058	39.843	1.216	***
	(0.112)	(0.121)	(0.164)	
Employment hours (weekly)	44.867	45.515	-0.649	**
	(0.185)	(0.179)	(0.259)	
Education	0.094	0.084	0.011	
< High School	(0.005)	(0.005)	(0.007)	
	0.293	0.309	-0.017	
High School	(0.008)	(0.008)	(0.011)	
	0.305	0.291	0.014	
Some College	(0.008)	(0.008)	(0.011)	
	0.308	0.316	-0.008	
≥College	(0.008)	(0.009)	(0.012)	

Note: *** indicates significance at the 1% level, ** 5% level, and * 10% level.

Table A.8: Descriptive Statistics of Body Mass Status, by Marital Status

Employment and child care Alternatives	Single	Married	Difference	
Obese (%)				
No work, no child care	21.013	13.090	7.923	***
	(1.574)	(0.503)	(1.437)	
No work, using child care	23.973	20.482	3.491	
	(3.545)	(3.142)	(4.720)	
Part-time, no child care	17.080	13.373	3.707	**
	(1.978)	(0.559)	(1.891)	
Part-time, using child care	24.643	13.410	11.233	***
	(2.580)	(1.219)	(2.556)	
Full-time, no child care	20.883	18.209	2.674	*
	(1.405)	(0.663)	(1.505)	
Full-time, using child care	20.546	17.126	3.420	***
	(1.083)	(0.718)	(1.270)	
Overweight (%)				
No work, no child care	38.599	27.471	11.128	***
	(1.881)	(0.666)	(1.870)	
No work, using child care	34.247	33.735	0.512	
	(3.941)	(3.681)	(5.391)	
Part-time, no child care	34.160	28.121	6.039	**
	(2.493)	(0.738)	(2.486)	
Part-time, using child care	41.071	29.119	11.953	***
	(2.945)	(1.625)	(3.238)	
Full-time, no child care	35.442	34.532	0.910	
	(1.653)	(0.816)	(1.837)	
Full-time, using child care	36.853	33.309	3.544	**
	(1.293)	(0.898)	(1.563)	
BMI-percentile				
No work, no child care	66.462	60.091	6.371	***
	(1.110)	(0.438)	(1.212)	
No work, using child care	63.426	64.434	-1.009	
	(2.519)	(2.424)	(3.502)	
Part-time, no child care	63.297	60.967	2.330	
	(1.552)	(0.472)	(1.586)	
Part-time, using child care	67.078	63.243	3.835	**
	(1.781)	(0.995)	(1.976)	
Full-time, no child care	66.330	64.958	1.372	
	(1.004)	(0.498)	(1.120)	
Full-time, using child care	67.751	63.847	3.905	***
	(0.757)	(0.553)	(0.946)	

Note: *** indicates significance at the 1% level, ** 5% level, and * 10% level.

Table A.9: Descriptive Statistics of Body Mass Status, by Income

	Income Category ($)			
Employment and Child Care Alternatives	0-25,000	25,000-50,000	50,000-75,000	>75,000
Obese (%)				
No work, no child care	20.87	17.14	13.59	7.02
No work, using child care	26.49	23.40	10.00	10.64
Part-time, no child care	23.48	16.35	11.81	10.47
Part-time, using child care	21.05	19.91	16.16	11.08
Full-time, no child care	22.92	21.90	16.74	14.89
Full-time, using child care	22.36	20.35	18.85	13.70
Overweight (%)				
No work, no child care	37.23	33.36	29.43	19.00
No work, using child care	37.75	31.91	35.00	25.53
Part-time, no child care	40.63	31.12	27.01	24.74
Part-time, using child care	37.65	37.17	33.62	24.65
Full-time, no child care	38.62	38.27	34.35	29.47
Full-time, using child care	37.46	37.83	34.99	29.38
BMI-percentile				
No work, no child care	66.19	63.04	61.10	55.28
No work, using child care	67.23	62.56	57.95	58.81
Part-time, no child care	66.27	62.89	60.59	58.98
Part-time, using child care	68.45	64.62	64.87	60.77
Full-time, no child care	67.43	67.21	64.94	62.36
Full-time, using child care	67.61	67.01	66.22	61.34

A.6 Sample Determination

In the first wave of the survey (i.e., in the fall of kindergarten in 1998-1999) there were 21,409 individuals that were surveyed. Of the 21,409 individual observations, those who were not missing the variables listed in Table A.10 (shown below) in any of the three analysis years (i.e., first third, and fifth grades) were kept in the sample. If during the three grades, BMI-percentile, lagged BMI-percentile, hours of employment and child care, and several child and mother characteristics were missing, the observations were dropped. As such, 6,330 individuals remained, resulting 18,990 individual-year observations.

Table A.10: Sample Determination

Dropped observations due to missing:	Observations Remaining
BMI-percentile-for-age-and-sex	9,768
Lagged BMI-percentile-for-age-and-sex	9,574
Hours of mother's employment	7,452
Hours of child care	7,451
Exogenous characteristics	6,330
(child's age, sex, race, number of siblings, and zipcode;	
(and mother's marital status and age)	
Total number of individuals	6,330
Total number of time periods	3
Total number of individual-year observations	18,990

Due to the loss of observations, I ran logit estimations of whether or not an individual attrited in one of the three survey years. That is, if an individual was dropped from the sample in either the first, third, or fifth grades. I then estimated a logit model using several observable characteristics such as: BMI-percentile-for-sex-and-age, race, age, mother and father's education and age. I found that compared to the original sample, the analysis dataset is slightly less likely to be black. However, there were no other variables that were significantly different between the two samples. More importantly, there were no differences in BMI-percentile-for-sex-and-age across the two samples.

A.7 Interaction Effects in Binary Outcome Models

Interaction effects[4] in linear models can be evaluated from the coefficient on the cross derivative. Specifically, suppose that the outcome y is a linear function of two variables x_1, x_2, and the interaction between the two variables. Then the expected value is

$$\mathrm{E}(y|x_1, x_2) = \beta_1 x_1 + \beta_{12} x_1 x_2 + \beta_2 x_2. \tag{A.20}$$

Assuming that x_1 and x_2 are continuous variables, the interaction effect can be expressed as

$$\frac{\partial^2 \mathrm{E}(y|x_1, x_2)}{\partial x_1 \partial x_2} = \beta_{12}. \tag{A.21}$$

However, when the model is non-linear (as in this paper, where the main equation of interest is a dichotomous outcome with the error term is Type-I Extreme value distributed) the interaction effect is not equal to the coefficient on the cross derivative. For example, suppose that the expected value of y is expressed as

$$\mathrm{E}(y|x_1, x_2) = \frac{\exp(\beta_1 x_1 + \beta_{12} x_1 x_2 + \beta_2 x_2)}{1 + \exp(\beta_1 x_1 + \beta_{12} x_1 x_2 + \beta_2 x_2)} \tag{A.22}$$

where x_1 and x_2 are continuous, independent variables. Then the interaction effect is written

$$\frac{\partial^2 \mathrm{E}(y|x_1, x_2)}{\partial x_1 \partial x_2} = \frac{\exp(\beta_1 + \beta_{12} + \beta_2)}{1 + \exp(\beta_1 + \beta_{12} + \beta_2)} - \frac{\exp(\beta_2)}{1 + \exp(\beta_2)} - \frac{\exp(\beta_2)}{1 + \exp(\beta_2)}. \tag{A.23}$$

Therefore, in this paper the interaction effect is estimated as

$$\frac{\partial^2 \mathrm{E}(y|x_1, x_2)}{\partial x_1 \partial x_2} = \frac{\exp(\widehat{\beta}_1 + \widehat{\beta}_{12} + \widehat{\beta}_2)}{1 + \exp(\widehat{\beta}_1 + \widehat{\beta}_{12} + \widehat{\beta}_2)} - \frac{\exp(\widehat{\beta}_1)}{1 + \exp(\widehat{\beta}_1)} - \frac{\exp(\widehat{\beta}_2)}{1 + \exp(\widehat{\beta}_2)} \tag{A.24}$$

[4]This discussion borrows from Ai and Norton (2003) and Norton et al. (2004)

A.8 Simulation Methods

Short Run versus Long Run Simulations

Two alternative results are presented in this paper: the short run effect, where individuals' observed histories in each period are used to simulate the body mass status outcomes; and the long run effect, where individuals' behaviors are updated each period using predicted outcomes from previous periods. The short run effect captures the immediate response of changes in employment and child care alternatives on the body mass status. On the other hand, the long run effect allows decisions made in previous periods to not only affect the current period, but also decisions and outcomes in future periods. Specifically, I first assign an individual to one employment and child care alternative in every period (i.e., first, third, and fifth grades). Then, I predict the body mass status outcome in first grade using the estimated parameters and the actual observed values. The predicted body mass outcome is then used to *update* the body mass outcome that is used to simulate health status in the third grade. This is repeated once more to predict body mass outcomes in the fifth grade, giving the long run predicted value of body mass status conditional on choosing one particular employment and child care alternative.

The estimation of the short run and long run effects are described in greater detail below.[5] To begin, the equations of interest are the following where the body mass status equation is

$$\text{Prob}(B_{t+1} = 1|\mu_2, \nu_{2t}) = \frac{\exp(\beta_0 + \beta_1 B_t + \beta_2 D_t + \beta_3 B_t D_t + \beta_4 X_t + \beta_5 P_t + \mu_2 + \nu_{2t})}{1 + \exp(\beta_0 + \beta_1 B_t + \beta_2 D_t + \beta_3 B_t D_t + \beta_4 X_t + \beta_5 P_t + \mu_2 + \nu_{2t})} \tag{A.25}$$

assuming that the idiosyncratic error term (e_{2t}) is serially uncorrelated and Type-I Extreme Value distributed. Given that the alternative employment and child care variables (D_t) are

[5] This assumes that the body mass outcome of interest is the probability that an individual is obese or overweight.

discrete variables the partial effect of D_t on the probability is

$$\begin{aligned}\frac{\Delta \text{Prob}(B_{t+1}=1|\mu_2,\nu_{2t})}{\Delta D_t} &= \text{Prob}(B_{t+1}=1|D_t=1)-\text{Prob}(B_{t+1}=1|D_t=0) \\ &= (\beta_2+\beta_3 B_t)\times \\ &\quad \frac{\exp(\beta_0+\beta_1 B_t+\beta_2 D_t+\beta_3 B_t D_t+\beta_4 X_t+\beta_5 P_t+\mu_2+\nu_{2t})}{[1+\exp(\beta_0+\beta_1 B_t+\beta_2 D_t+\beta_3 B_t D_t+\beta_4 X_t+\beta_5 P_t+\mu_2+\nu_{2t})]^2}\end{aligned} \tag{A.26}$$

Empirical Implementation of the Short and Long Run Effects

Short Run Effects with no updating

Model 1 does not control for any potential unobservable variables whereas model 2 controls for permanent individual heterogeneity. Both models were estimated using STATA. To obtain short run effects and standard errors, a non-parametric bootstrapping technique is applied as follows:

1. Draw (with replacement) a sample of size N, where N is the number of individual-year observations (i.e., 22,329).

2. Using the drawn sample, estimate $\widehat{\beta}=[\widehat{\beta}_0,\widehat{\beta}_1,...]$.

3. Set D_{it}=1 and $B_{it}D_{it}$=1 and predict $\text{Prob}(B_{it+1}=1|D_{it}=1)$ for each individual in each time period, that is $\text{Prob}(\widehat{B_{it+1}}=1|D_{it}=1)$.

4. Set D_{it}=0 and $B_{it}D_{it}$=0 and predict $\text{Prob}(B_{it+1}=1|D_{it}=0)$ for each individual in each time period, that is $\text{Prob}(\widehat{B_{it+1}}=1|D_{it}=0)$.

5. Estimate the short run effect for each individual in each time period as:

$$\frac{\Delta \text{Prob}(\widehat{B_{it+1}}=1)}{\Delta D_{it}}=\text{Prob}(\widehat{B_{it+1}}=1|D_{it}=1)-\text{Prob}(\widehat{B_{it+1}}=1|D_{it}=0) \tag{A.27}$$

6. Take the average short run effect over all individuals and over time, specifically:

$$\frac{\Delta \text{Prob}(\widehat{B}=1)}{\Delta D} = \frac{1}{N}\sum_{i=1}^{N}\left[\frac{1}{T}\sum_{t=1}^{T}\frac{\Delta \text{Prob}(\widehat{B_{it+1}}=1)}{\Delta D_{it}}\right]$$

7. Repeat steps 1 through 6 R independent times, where R is the total number of bootstrap replications (in this paper, R=200).

8. Using the R bootstrap replications, the bootstrapped statistic is estimated.

Long Run Effects with updating

Long run simulation effects are also evaluated using a non-parametric bootstrap method where the procedure is as follows:

1. Draw (with replacement) a sample of size N, where N is the number of individual-year observations (i.e., 22,329).

2. Using the drawn sample, estimate $\widehat{\beta} = [\widehat{\beta}_0, \widehat{\beta}_1, ...]$.

3. Assign employment and child care to one category (e.g., let D_{it}=1), and set D_1=1 and B_1D_1=1.

4. Using observed variables in the first wave (i.e., first grade) and estimated coefficients, predict body mass status observed at the end of the first grade period (B_{i2}): $\text{Prob}(\widehat{B_{i1}} = 1|D_{i1} = 1)$ for each individual in each time period.

5. Draw a number e from a uniform distribution. If $e < \text{Prob}(\widehat{B_{i1}} = 1|D_{i1} = 1)$ then set $\widehat{B}_{i1} = 1$ and 0 otherwise.

6. Repeat steps 4 and 5 for T periods (in this case, 3 periods), that is update body mass status used in step 4 to that predicted in step 5.

7. Repeat steps 1 through 6 R independent times, where R is the total number of bootstrap replications (in this paper, R=200).

8. Using the R bootstrap replications, the bootstrapped statistic is estimated.

Estimation for Model 3

Model 3 is the preferred model, where the body mass status outcome is estimated jointly with the employment and child care decision equation. Simulations for this model are done using a technique that is a combination of both a parametric and a non-parametric bootstrap method.

Long Run Effects: with updating

1. Follow steps 1 through 3 for the short run effects (with updating).

2. Assign employment and child care to one category (e.g., let D_{it}=1), and set D_1=1 and B_1D_1=1.

3. Using observed variables in the first wave (i.e., first grade) and estimated coefficients, predict body mass status observed at the end of the first grade period (B_{i2}): $\text{Prob}(\widehat{B_{i1}} = 1|D_{i1} = 1, \widehat{\mu}_{2i}, \widehat{\nu}_{2it})$ for each individual in each time period.

4. Draw a number e from a uniform distribution. If $e < \text{Prob}(\widehat{B_{i1}} = 1|D_{i1} = 1, \widehat{\mu}_{2i}, \widehat{\nu}_{2it})$ then set $\widehat{B}_{i1} = 1$ and 0 otherwise.

5. Repeat steps 4 and 5 for T periods (in this case, 3 periods), that is update body mass status used in step 4 to that predicted in step 5.

6. Repeat steps 1 through 5 R independent times, where R is the total number of bootstrap replications (in this paper, R=200).

7. Using the R bootstrap replications, the bootstrapped statistic is estimated.

A.9 Unobserved Heterogeneity Parameters

The preferred model in this paper is joint estimation of the employment and child care alternatives and the body mass status outcome equations. The joint estimation was conducted using a discrete factor estimation technique, which is a flexible random-effects maximum likelihood estimation technique. In this paper, I control for both permanent (time-invariant) and time-varying unobserved heterogeneity semi-parametrically in the body mass outcome equation, employment and child care alternative equation, and the initial condition equation.[6] Mass points are added until the likelihood function failed to improve and until the coefficient estimates failed to change.

The first mass point was fixed at zero for all estimations. The probability of obesity outcome was estimated using 9 permanent and 4 time-varying heterogeneity mass points, the probability of being overweight outcome with 6 permanent and 4 time-varying mass points, and the BMI-percentile outcome with 4 permanent and 4 time-varying mass points. In Tables A.11-A.12, I present mass points and probabilities for time-invariant and time-varying heterogeneity parameters, respectively, for the obesity outcome. Similarly for Tables A.13-A.16, I present the mass point and probabilities for estimations where the outcomes are risk of being overweight and BMI-percentile.

[6] In the initial condition equation, the time-varying heterogeneity parameters were fixed at zero.

Table A.11: Coefficient Estimates for Permanent Individual Level Heterogeneity Parameters (Outcome: Risk of Obesity)

			Employment and Child Care Decision					
Mass Point	Prob	Risk of Obese	No work using child care	Part-time, not using child care	Part-time, using child care	Full-time, not using child care	Full-time using child care	Initial Condition
1	7.99	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)
2	17.39	-0.01	-0.04	7.18	11.99	12.11	13.76	-0.36
		(0.31)	(1.64)	(0.84)	(2.21)	(0.96)	(0.91)	(0.39)
3	8.53	-0.57	0.44	5.84	9.39	4.35	5.52	-1.53
		(0.37)	(1.31)	(0.65)	(2.13)	(0.81)	(0.70)	(0.56)
4	23.15	0.06	0.71	5.47	6.84	8.04	7.15	-0.28
		(0.29)	(1.18)	(0.59)	(2.26)	(0.70)	(0.67)	(0.41)
5	11.45	-2.00	-0.78	2.98	2.85	0.87	-1.47	-37.79
		(0.69)	(2.25)	(0.42)	(2.21)	(0.60)	(0.84)	(1.00)
6	7.60	-0.57	3.22	-49.11	7.07	4.81	7.49	-1.25
		(0.41)	(1.25)	(1.00)	(2.17)	(0.75)	(0.76)	(0.68)
7	9.15	-1.34	1.04	-1.03	0.13	-3.23	-3.82	-2.28
		(0.47)	(1.53)	(0.49)	(2.34)	(0.77)	(0.75)	(0.93)
8	8.35	-0.10	-59.13	7.95	7.92	6.73	6.34	-0.72
		(0.36)	(1.00)	(0.81)	(2.21)	(0.98)	(0.93)	(0.51)
9	6.39	0.44	-1.47	3.26	4.17	-1.11	-0.14	0.44
		(0.39)	(1.94)	(0.52)	(2.16)	(1.48)	(0.72)	(0.61)

Table A.12: Coefficient Estimates for Time-varying Heterogeneity Parameters (Outcome: Risk of Obesity)

			Employment and Child Care Decision					
Mass Point	Prob	Risk of Obese	No work using child care	Part-time, not using child care	Part-time, using child care	Full-time, not using child care	Full-time using child care	Initial Condition
1	2.45	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)
2	91.06	-0.42	60.40	0.86	15.57	7.87	32.11	0.00
		(0.58)	(3.99)	(1.21)	(4.00)	(1.79)	(3.54)	(Fixed)
3	3.10	-0.95	65.31	-4.14	0.61	0.99	0.10	0.00
		(0.79)	(4.41)	(2.22)	(8.50)	(2.40)	(1.00)	(Fixed)
4	3.39	-0.29	0.10	-5.83	9.32	-0.98	0.10	0.00
		(0.73)	(1.00)	(1.82)	(3.97)	(2.13)	(1.00)	(Fixed)

Table A.13: Coefficient Estimates for Permanent Individual Level Heterogeneity Parameters (Outcome: Risk of Overweight)

			Employment and Child Care Decision					
Mass Point	Prob	Risk of Overweight	No work using child care	Part-time, not using child care	Part-time, using child care	Full-time, not using child care	Full-time using child care	Initial Condition
1	11.83	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)
2	23.00	0.83	1.12	7.01	11.93	14.11	0.88	78.34
		(0.32)	(0.80)	(0.58)	(0.70)	(0.74)	(19.08)	(0.52)
3	10.47	0.69	-0.77	8.29	10.65	7.89	9.39	77.77
		(0.32)	(0.82)	(0.42)	(0.54)	(0.53)	(0.57)	(0.54)
4	27.39	1.02	-1.66	6.92	7.78	11.20	10.78	78.39
		(0.31)	(0.80)	(0.37)	(0.59)	(0.56)	(0.63)	(0.52)
5	21.54	0.83	-4.58	4.14	3.06	3.19	2.21	78.11
		(0.30)	(1.07)	(0.20)	(0.41)	(0.32)	(0.43)	(0.53)
6	5.77	1.69	-0.12	0.23	-0.05	0.13	0.62	80.35
		(0.33)	(0.68)	(0.29)	(0.55)	(0.46)	(0.52)	(0.78)

Table A.14: Coefficient Estimates for Time-varying Heterogeneity Parameters (Outcome: Risk of Overweight)

			Employment and Child Care Decision					
Mass Point	Prob	Risk of Overweight	No work using child care	Part-time, not using child care	Part-time, using child care	Full-time, not using child care	Full-time using child care	Initial Condition
1	3.18	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)
2	86.11	-0.28	22.95	20.57	10.53	12.31	29.65	0.00
		(0.31)	(5.11)	(18.27)	(2.56)	(1.48)	(4.80)	(Fixed)
3	1.56	-0.47	30.84	-19.03	5.26	-17.08	0.10	0.00
		(0.60)	(5.38)	(1.00)	(2.57)	(1.00)	(1.00)	(Fixed)
4	9.15	-0.12	0.10	19.65	6.02	6.91	0.10	0.00
		(0.36)	(1.00)	(18.28)	(3.21)	(1.50)	(1.00)	(Fixed)

Table A.15: Coefficient Estimates for Permanent Individual Level Heterogeneity Parameters (Outcome: BMI-Percentile)

			Employment and Child Care Decision					
Mass Point	Prob	Pred BMI	No work using child care	Part-time, not using child care	Part-time, using child care	Full-time, not using child care	Full-time using child care	Initial Condition
1	24.25	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)
2	25.50	1.75	-28.35	9.47	10.06	9.92	8.86	1.41
		(0.73)	(1.00)	(0.89)	(0.89)	(0.96)	(0.89)	(1.44)
3	20.32	1.00	2.33	-0.81	6.84	1.79	9.26	1.35
		(0.71)	(0.59)	(1.43)	(0.75)	(1.36)	(0.74)	(1.64)
4	29.93	2.02	2.25	10.12	10.81	15.69	13.71	4.68
		(0.93)	(0.91)	(0.90)	(0.90)	(1.09)	(0.89)	(1.32)

Table A.16: Coefficient Estimates for Time-varying Heterogeneity Parameters (Outcome: BMI-Percentile)

			Employment and Child Care Decision					
Mass Point	Prob	Pred BMI	No work using child care	Part-time, not using child care	Part-time, using child care	Full-time, not using child care	Full-time using child care	Initial Condition
1	79.35	0.00	0.00	0.00	0.00	0.00	0.00	0.00
		(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)	(Fixed)
2	5.15	-1.58	-0.21	-9.49	-25.79	-55.85	-12.38	0.00
		(1.47)	(0.93)	(1.12)	(12.64)	(8.78)	(1.34)	(Fixed)
3	15.51	-0.37	-9.82	8.64	-76.83	11.27	-0.73	0.00
		(1.41)	(5.40)	(1.17)	(1.00)	(1.26)	(1.24)	(Fixed)

A.10 Additional Tables

Table A.17: Coefficients from Obesity Equation

Variable	Model 1c			Model 2c			Model 3		
No work, using child care	-0.04	(0.29)		0.01	(0.02)		0.24	(0.46)	
Part-time, no child care	-0.01	(0.11)		-0.01	(0.01)		-0.31	(0.19)	*
Part-time, using child care	0.20	(0.16)		0.00	(0.01)		-0.02	(0.26)	
Full-time, no child care	0.04	(0.11)		-0.01	(0.01)		-0.51	(0.22)	**
Full-time, using child care	0.19	(0.11)	*	-0.01	(0.01)		-0.31	(0.25)	
Current Health	4.75	(0.14)	***	-0.02	(0.01)		4.32	(0.19)	***
Current Health ×									
No work, using child care	0.51	(0.56)		0.01	(0.04)		0.70	(0.58)	
Part-time, no child care	0.05	(0.21)		0.02	(0.02)		0.17	(0.24)	
Part-time, using child care	-0.22	(0.31)		0.01	(0.03)		0.02	(0.34)	
Full-time, no child care	0.01	(0.19)		-0.02	(0.02)		0.38	(0.23)	*
Full-time, using child care	0.02	(0.20)		0.01	(0.02)		0.41	(0.23)	*
Child characteristics									
Male	0.33	(0.06)	***	-			0.36	(0.06)	***
Age	0.53	(0.51)		0.06	(0.04)		0.52	(0.51)	
Age squared	-0.03	(0.03)		0.01	(0.00)	**	-0.03	(0.03)	
Black	0.27	(0.11)	**	-			0.29	(0.12)	**
Hispanic	0.20	(0.09)	**	-			0.23	(0.09)	**
Siblings	-0.06	(0.03)	**	0.01	(0.01)		-0.07	(0.03)	**
Mother characteristics									
Age	0.01	(0.01)	*	0.01	(0.01)		0.01	(0.01)	
Education									
High School	0.00	(0.12)		0.03	(0.02)	*	0.04	(0.13)	
Some College	-0.04	(0.12)		0.04	(0.02)	**	0.00	(0.13)	
$\geq$ College	-0.22	(0.14)	*	0.04	(0.02)	*	-0.19	(0.15)	
Married	-0.11	(0.14)		-0.02	(0.01)		-0.13	(0.14)	
Prior Work	0.03	(0.08)		-					

Table A.17 (continued)

Variable	Model 1c			Model 2c			Model 3		
Father characteristics							0.16	(0.10)	
Age	-0.01	(0.01)		0.01	(0.01)		0.00	(0.01)	
Education									
High School	-0.19	(0.12)		0.01	(0.02)		-0.18	(0.13)	
Some College	-0.30	(0.13)	**	0.01	(0.02)		-0.28	(0.13)	**
$\geq$ College	-0.71	(0.14)	***	-0.02	(0.02)		-0.73	(0.14)	***
Time Dummy: Third Grade	0.55	(0.23)	**	0.02	(0.06)		0.62	(0.24)	***
Time Dummy: Fifth Grade	0.52	(0.36)		0.06	(0.12)		0.62	(0.37)	*
Food and Activity Price and Availability									
Fast Food Price	0.02	(0.03)		0.01	(0.01)		0.01	(0.03)	
Restaurant Price	-0.22	(0.14)		-0.06	(0.02)	***	-0.25	(0.15)	*
# of Limited Service Restaurants	0.28	(0.28)		0.09	(0.04)	**	0.35	(0.29)	
# of Full Service Restaurants	-0.28	(0.19)		-0.05	(0.03)		-0.33	(0.19)	*
# of Supermarkets	-0.69	(0.89)		-0.20	(0.11)	**	-0.46	(0.92)	
# of Convenience Stores	1.21	(0.51)	**	0.09	(0.07)		1.40	(0.53)	***
# of Fitness Centers	0.66	(0.45)		-0.08	(0.06)		0.72	(0.46)	
Constant	-5.11	(2.39)	**	0.03	(0.27)		-4.09	(2.49)	*

Note: Standard errors in parentheses. *** indicates significance at 1%, ** 5%, and * 10%.

Table A.18: Coefficients from Overweight Equation

Variable	Model 1c			Model 2c			Model 3		
No work, using child care	-0.55	(0.28)	**	-0.02	(0.02)		-0.40	(0.43)	
Part-time, no child care	-0.01	(0.08)		-0.02	(0.01)	**	-0.17	(0.13)	
Part-time, using child care	0.09	(0.13)		0.00	(0.02)		0.03	(0.21)	
Full-time, no child care	-0.03	(0.08)		-0.02	(0.01)	*	-0.29	(0.18)	*
Full-time, using child care	0.15	(0.08)	**	-0.02	(0.01)		-0.02	(0.23)	
Current Health	3.93	(0.10)	***	-0.04	(0.01)	***	3.46	(0.12)	***
Current Health ×									
No work, using child care	1.04	(0.46)	**	0.05	(0.04)		1.07	(0.47)	**
Part-time, no child care	-0.06	(0.14)		-0.01	(0.02)		0.34	(0.15)	**
Part-time, using child care	-0.20	(0.21)		0.00	(0.03)		0.21	(0.22)	
Full-time, no child care	0.21	(0.14)		0.00	(0.02)		0.65	(0.15)	***
Full-time, using child care	0.01	(0.14)		0.02	(0.02)		0.45	(0.15)	***
Child characteristics									
Male	0.17	(0.05)		-			0.18	(0.05)	***
Age	0.17	(0.38)		-0.02	(0.05)		0.17	(0.38)	
Age squared	-0.01	(0.02)		0l.01	(0.01)		-0.01	(0.02)	
Black	0.17	(0.09)	**	-			0.18	(0.09)	**
Hispanic	0.19	(0.07)	***	-			0.22	(0.07)	***
Siblings	-0.07	(0.02)	***	-0.01	(0.01)		-0.07	(0.02)	***
Mother characteristics									
Age	0.00	(0.01)		0.01	(0.01)		0.00	(0.01)	
Education									
High School	-0.06	(0.10)		0.04	(0.02)	*	-0.07	(0.10)	
Some College	-0.10	(0.10)		0.08	(0.03)	***	-0.11	(0.10)	
$\geq$ College	-0.39	(0.11)	***	0.07	(0.03)	**	-0.40	(0.11)	
Married	0.03	(0.11)		-0.02	(0.02)		0.05	(0.11)	
Prior Work	-0.03	(0.06)		-			-0.01	(0.09)	

Table A.18 (continued)

Variable	Model 1c			Model 2c			Model 3		
Father characteristics									
Age	0.00	(0.00)		0.01	(0.01)		0.00	(0.00)	
Education									
High School	-0.09	(0.10)		0.04	(0.02)	*	-0.09	(0.10)	
Some College	-0.22	(0.10)	**	0.06	(0.02)	**	-0.21	(0.10)	**
≥ College	-0.34	(0.11)	***	0.08	(0.03)	***	-0.34	(0.11)	***
Time Dummy: Third Grade	0.74	(0.17)	***	0.13	(0.08)	*	0.76	(0.18)	***
Time Dummy: Fifth Grade	0.62	(0.27)	**	0.24	(0.15)		0.65	(0.28)	**
Food and Activity Price and Availability									
Fast Food Price	0.01	(0.02)		0.01	(0.01)		0.00	(0.02)	
Restaurant Price	-0.16	(0.11)		-0.07	(0.03)	**	-0.19	(0.11)	*
# of Limited Service Restaurants	0.13	(0.21)		0.10	(0.05)	**	0.12	(0.22)	
# of Full Service Restaurants	-0.04	(0.14)		-0.05	(0.04)		-0.05	(0.14)	
# of Supermarkets	-1.04	(0.67)		-0.15	(0.14)		-0.96	(0.68)	
# of Convenience Stores	0.88	(0.39)	**	0.11	(0.09)		1.03	(0.40)	***
# of Fitness Centers	0.37	(0.35)		-0.16	(0.08)	**	0.39	(0.35)	
Constant	-2.70	(1.78)		0.54	(0.36)		-3.08	(1.84)	*

Note: Standard errors in parentheses. *** indicates significance at 1%, ** 5%, and * 10%.

Table A.19: Coefficients from BMI-Percentile Equation

Variable	Model 1c			Model 2c			Model 3		
No work, using child care	-2.89	(2.15)		0.15	(2.17)		-3.06	(2.15)	
Part-time, no child care	-0.40	(0.78)		-1.32	(0.92)		-1.61	(1.09)	
Part-time, using child care	0.01	(1.33)		-2.77	(1.47)	*	-1.46	(1.47)	
Full-time, no child care	0.24	(0.80)		-1.52	(1.01)		-1.28	(1.51)	
Full-time, using child care	1.01	(0.81)		-0.62	(1.07)		-0.32	(1.08)	
Current Health	0.83	(0.01)	***	-0.01	(0.01)		0.83	(0.01)	***
Current Health ×									
No work, using child care	0.04	(0.03)		0.00	(0.03)		0.04	(0.03)	
Part-time, no child care	0.01	(0.01)		0.01	(0.01)		0.01	(0.01)	
Part-time, using child care	0.00	(0.02)		0.03	(0.02)		0.00	(0.02)	
Full-time, no child care	0.01	(0.01)		0.01	(0.01)		0.01	(0.01)	
Full-time, using child care	0.00	(0.01)		0.01	(0.02)		0.00	(0.01)	
Child characteristics									
Male	1.01	(0.23)	***	(dropped)			1.01	(0.23)	***
Age	1.11	(1.86)		-4.31	(2.41)	*	1.03	(1.85)	
Age squared	-0.06	(0.10)		-0.04	(0.08)		-0.06	(0.10)	
Black	1.41	(0.46)	***	(dropped)			1.49	(0.46)	***
Hispanic	0.72	(0.36)	**	(dropped)			0.73	(0.36)	**
Siblings	-0.22	(0.11)	**	-0.29	(0.34)		-0.24	(0.11)	**
Mother characteristics									
Age	-0.01	(0.03)		0.10	(0.09)		-0.02	(0.03)	
Education									
High School	-0.36	(0.51)		3.31	(1.15)	***	-0.30	(0.51)	
Some College	-0.54	(0.52)		4.71	(1.27)	***	-0.48	(0.51)	
≥ College	-1.62	(0.56)	***	5.46	(1.57)	***	-1.57	(0.56)	***
Married	0.67	(0.57)		-0.67	(0.73)		0.63	(0.57)	
Prior Work	-0.21	(0.30)		(dropped)			0.24	(0.40)	

Table A.19 (continued)

Variable	Model 1c			Model 2c			Model 3		
Father characteristics									
Age	0.01	(0.02)		-0.20	(0.12)	*	0.01	(0.02)	
Education									
High School	-0.91	(0.53)	*	-0.56	(1.05)		-0.85	(0.52)	*
Some College	-1.36	(0.54)	***	0.34	(1.14)		-1.33	(0.53)	**
$\geq$ College	-1.81	(0.57)	***	0.87	(1.28)		-1.78	(0.55)	***
Time Dummy: Third Grade	3.05	(0.85)	***	13.39	(3.80)	***	3.13	(0.85)	***
Time Dummy: Fifth Grade	2.59	(1.38)	*	26.00	(7.43)	***	2.71	(1.38)	**
Food and Activity Price and Availability									
Fast Food Price	0.16	(0.11)		0.77	(0.40)	**	0.15	(0.11)	
Restaurant Price	-1.41	(0.54)	***	-6.90	(1.52)	***	-1.42	(0.54)	***
# of Limited Service Restaurants	2.46	(1.09)	**	8.34	(2.24)	***	2.45	(1.09)	**
# of Full Service Restaurants	-1.75	(0.72)	**	-5.59	(2.02)	***	-1.76	(0.72)	**
# of Supermarkets	-8.80	(3.43)	***	-23.37	(6.67)	***	-8.59	(3.43)	**
# of Convenience Stores	5.39	(2.00)	***	8.59	(4.45)	**	5.38	(2.00)	***
# of Fitness Centers	-1.14	(1.78)		-9.91	(3.86)	***	-1.02	(1.78)	
Constant	9.98	(8.75)		115.23	(17.36)	***	10.02	(8.74)	

Note: Standard errors in parentheses. *** indicates significance at 1%, ** 5%, and * 10%.

Appendix to Chapter 2

B.1 Empirical Specification for the Cognitive Outcome Equation

The cognitive outcome equations for reading (R_t) and math (M_t) scores are jointly estimated with the employment and child care equation (D_t) in this model specification. This specification allows for the possibility that the error terms in the reading and math equations are correlated (in addition to the correlation between the error terms in the cognitive outcome equations and the employment and child care decision equation). Specifically, if there are unobservable characteristics of the mother or child, such as a child's motivation and ability (factors which are not observable in the data by the econometrician), that is correlated with the child's reading scores then it is very likely that such a factor is also related to the child's math scores. Estimation of the two cognitive outcomes therefore allows for such a relationship across equations.

In estimation, I control for two sources of unobserved heterogeneity: permanent (μ) and time-varying heterogeneity (ν_t). The error terms for the employment and child care decision equation (ϵ_{1t}^d), the reading score equation (ϵ_{2t}^R), and math score equation (ϵ_{2t}^M) is decomposed into three components

$$\begin{aligned} \epsilon_{1t}^d &= \mu_1^d + \nu_{1t}^d + e_{1t}^d \quad d = 0, ..., 7 \\ \epsilon_{2t}^C &= \mu_2^C + \nu_{2t}^C + e_{2t}^C \quad C = R, M \end{aligned} \tag{B.1}$$

where μ_1^d and μ_2^C capture time-invariant unobserved heterogeneity, ν_{1t}^d and ν_{2t}^C capture time-varying unobserved heterogeneity components, and e_{1t}^d and e_{2t}^C represent the remaining error components that are identically and independently distributed.

I assume that e_{1t}^d is Type-I Extreme Value distributed so that maternal employment and child care choices probabilities, conditional on the unobserved heterogeneity components (μ_1 and ν_{1t}) can be written (in log odds) as

$$\ln\left[\frac{\Pr(D_t = d|\mu_1, \nu_{1t})}{\Pr(D_t = 0|\mu_1, \nu_{1t})}\right] = \gamma_{0d} + \gamma_{1d}B_t + \gamma_{2d}X_t + \gamma_{3d}P_t + \gamma_{4d}Z_t + \mu_1^d + \nu_{1t}^d \quad d = 1, ..., 7. \tag{B.2}$$

Furthermore, I assume that e_{2t}^R and e_{2t}^M are normally distributed with mean zero and standard deviation σ_R and σ_M, respectively.

The unconditional likelihood function for individual i is

$$\begin{aligned}\mathrm{L}_i(\Theta,\psi,\pi) &= \sum_{k=1}^{K}\pi_k\Bigg\{\phi(R_1|\mu_{2k}^R)\phi(M_1|\mu_{2k}^M)\prod_{t=1}^{T}\sum_{\ell=1}^{L}\psi_\ell\Bigg[\prod_{d=0}^{7}\Pr(D_t=d|\mu_{1k}^d,\nu_{1t\ell}^d)\mathbf{1}[D_{it}=d]\\ &\times \qquad \phi(R_{t+1}|\mu_{2k}^R,\nu_{2t\ell}^R)\phi(M_{t+1}|\mu_{2k}^M,\nu_{2t\ell}^M)\Bigg]\Bigg\}\end{aligned} \tag{B.3}$$

where $Theta$ is the vector of variables to be estimated. ϕ is the probability density function for a normal distribution, for $C = R, M$, given by

$$\phi(C|\mu_2^C,\nu_{2t}^C) = \frac{1}{\sqrt{2\Pi\sigma_c^2}}\exp\Bigg(-\frac{(\beta_0+\beta_1C_t+\beta_2D_t+\beta_3C_tD_t+\beta_4X_t+\beta_5P_t+\mu_2^C+\nu_{2t}^C)^2}{2\sigma_C^2}\Bigg) \tag{B.4}$$

conditional on the unobserved heterogeneity components.

The distribution of π_k and ψ_ℓ are given by

$$\begin{aligned}\pi_k &= \Pr(\mu_1^0=\mu_{1k}^0,...\mu_1^7=\mu_{1k}^7,\mu_2^R=\mu_{2k}^R,\mu_2^M=\mu_{2k}^M) \quad k=1,...,K\\ \psi_\ell &= \Pr(\nu_{1t}^0=\nu_{1t\ell}^0,...\nu_{1t}^7=\nu_{1t\ell}^7,\nu_{2t}^R=\nu_{2t\ell}^R,\nu_{2t}^M=\nu_{2t\ell}^M) \quad \ell=1,...,L,\forall t\end{aligned} \tag{B.5}$$

where K is the number of time-invariant mass points and L is the total number of time-varying mass points.

B.2 Additional Tables

Table B.1: Coefficients from Obesity Equation (by child care mode: informal versus formal)

Variable	Model 1c			Model 2c			Model 3		
No work, use child care (informal or formal)	0.02	(0.29)		0.01	(0.02)		-0.18	(0.30)	
Part-time, no child care	-0.03	(0.11)		-0.01	(0.01)		-0.28	(0.15)	*
Part-time, informal child care	0.28	(0.19)		-0.01	(0.01)		-0.03	(0.23)	
Part-time, formal child care	-0.01	(0.28)		0.02	(0.02)		-0.38	(0.44)	
Full-time, no child care	0.03	(0.11)		-0.01	(0.01)		-0.46	(0.17)	***
Full-time, informal child care	0.17	(0.12)		-0.01	(0.01)		-0.26	(0.18)	
Full-time, formal child care	0.20	(0.14)		-0.01	(0.01)		-0.30	(0.22)	
Current Health	4.76	(0.14)	***	-0.02	(0.02)		4.72	(0.15)	***
Current Health ×									
No work, using child care (formal, informal)	0.41	(0.57)		0.01	(0.04)		0.42	(0.57)	
Part-time, no child care	0.01	(0.21)		0.01	(0.02)		0.03	(0.21)	
Part-time, using informal child care	0.13	(0.39)		0.04	(0.03)		0.17	(0.39)	
Part-time, using formal child care	-0.99	(0.49)	**	-0.12	(0.05)	***	-0.95	(0.50)	*
Full-time, no child care	0.00	(0.20)		-0.02	(0.02)		0.03	(0.20)	
Full-time, using informal child care	-0.06	(0.22)		0.00	(0.02)		-0.02	(0.23)	
Full-time, using formal child care	0.09	(0.30)		0.01	(0.03)		0.13	(0.30)	
Child characteristics									
Male	0.33	(0.06)	***	-			0.34	(0.06)	***
Age	0.53	(0.51)		0.06	(0.04)		0.49	(0.51)	
Age squared	-0.03	(0.03)		0.01	0.01	**	-0.03	(0.03)	
Black	0.27	(0.11)	**	-			0.30	(0.11)	***
Hispanic	0.20	(0.09)	**	-			0.21	(0.09)	**
Siblings	-0.06	(0.03)	**	0.01	(0.01)		-0.07	(0.03)	**

Table B.1 (continued)

Variable	Model 1c			Model 2c			Model 3		
Mother characteristics									
Age	0.01	(0.01)	*	0.01	0.01		0.01	(0.01)	
Education									
High School	0.01	(0.12)		0.03	(0.02)	*	0.03	(0.12)	
Some College	-0.03	(0.12)		0.04	(0.02)	**	-0.01	(0.13)	
≥ College	-0.21	(0.14)		0.04	(0.02)	*	-0.19	(0.14)	
Married	-0.11	(0.14)		-0.02	(0.01)		-0.11	(0.14)	
Prior Work	0.04	(0.08)		-			0.18	(0.09)	**
Father characteristics									
Age	-0.01	(0.01)		0.01	(0.01)		-0.01	(0.01)	
Education									
High School	-0.19	(0.12)		0.01	(0.02)		-0.16	(0.13)	
Some College	-0.30	(0.13)	**	0.01	(0.02)		-0.28	(0.13)	**
≥ College	-0.71	(0.14)	***	-0.02	(0.02)		-0.70	(0.14)	***
Time Dummy: Third Grade	0.54	(0.23)	**	0.02	(0.06)		0.60	(0.23)	***
Time Dummy: Fifth Grade	0.50	(0.36)		0.05	(0.12)		0.58	(0.36)	
Food and Activity Price and Availability									
Fast Food Price	0.01	(0.03)		0.01	(0.01)		0.01	(0.03)	
Restaurant Price	-0.21	(0.14)		-0.06	(0.02)	***	-0.22	(0.14)	
# of Limited Service Restaurants	0.29	(0.28)		0.09	(0.04)	**	0.32	(0.28)	
# of Full Service Restaurants	-0.28	(0.19)		-0.05	(0.03)		-0.28	(0.19)	
# of Supermarkets	-0.71	(0.89)		-0.20	(0.11)	**	-0.73	(0.90)	
# of Convenience Stores	1.20	(0.51)	**	0.09	(0.07)		1.23	(0.51)	**
# of Fitness Centers	0.70	(0.45)		-0.07	(0.06)		0.69	(0.45)	
Constant	-0.19	(0.19)		0.02	(0.27)		-5.31	(2.47)	**

Table B.2: Coefficients from Overweight Equation (by child care mode: informal versus formal)

Variable	Model 1c			Model 2c			Model 3		
No work, use child care (informal or formal)	-0.54	(0.29)	*	-0.03	(0.02)		-0.82	(0.31)	***
Part-time, no child care	0.02	(0.08)		-0.02	(0.01)	*	-0.09	(0.14)	
Part-time, informal child care	0.13	(0.16)		-0.01	(0.02)		-0.33	(0.19)	*
Part-time, formal child care	0.01	(0.22)		0.01	(0.02)		0.21	(0.39)	
Full-time, no child care	-0.01	(0.08)		-0.02	(0.01)		-0.47	(0.16)	***
Full-time, informal child care	0.20	(0.09)	**	-0.01	(0.01)		-0.17	(0.15)	
Full-time, formal child care	0.09	(0.12)		-0.03	(0.02)	*	-0.69	(0.19)	***
Current Health	3.95	(0.10)	***	-0.04	(0.01)	***	3.28	(0.13)	***
Current Health ×									
No work, using child care (formal, informal)	1.00	(0.46)	**	0.05	(0.04)		1.27	(0.48)	***
Part-time, no child care	-0.11	(0.14)		-0.01	(0.02)		0.15	(0.17)	
Part-time, using informal child care	0.02	(0.26)		0.01	(0.03)		0.62	(0.28)	**
Part-time, using formal child care	-0.73	(0.34)	**	-0.04	(0.04)		-0.13	(0.37)	
Full-time, no child care	0.19	(0.14)		0.00	(0.02)		0.69	(0.17)	***
Full-time, using informal child care	0.12	(0.17)		0.03	(0.02)	*	0.67	(0.19)	***
Full-time, using formal child care	-0.23	(0.19)		-0.01	(0.03)		0.30	(0.21)	
Child characteristics									
Male	0.17	(0.05)	***	-			0.18	(0.05)	***
Age	0.16	(0.38)		-0.02	(0.05)		0.16	(0.39)	
Age squared	-0.01	(0.02)		0.00	0.00		-0.01	(0.02)	
Black	0.17	(0.09)	**	-			0.20	(0.10)	**
Hispanic	0.19	(0.07)	***	-			0.26	(0.07)	***
Siblings	-0.07	(0.02)	***	-0.01	(0.01)		-0.09	(0.02)	***

Table B.2 (continued)

Variable	Model 1c			Model 2c			Model 3		
Mother characteristics									
Age	0.01	(0.01)		0.01	(0.01)		0.01	(0.01)	
Education									
High School	-0.06	(0.10)		0.04	(0.02)	*	-0.06	(0.10)	
Some College	-0.09	(0.10)		0.08	(0.03)	***	-0.08	(0.11)	
$\geq$ College	-0.38	(0.11)	***	0.07	(0.03)	**	-0.38	(0.12)	***
Married	0.03	(0.11)		-0.02	(0.02)		-0.01	(0.11)	
Prior Work	-0.03	(0.06)		-			0.06	(0.07)	
Father characteristics									
Age	0.01	(0.01)		0.01	(0.01)		-0.01	(0.01)	
Education									
High School	-0.09	(0.10)		0.04	(0.02)	*	-0.07	(0.11)	
Some College	-0.22	(0.10)	**	0.06	(0.02)	**	-0.20	(0.11)	**
$\geq$ College	-0.34	(0.11)	***	0.08	(0.03)	***	-0.35	(0.12)	***
Time Dummy: Third Grade	0.75	(0.17)	***	0.13	(0.08)	*	0.78	(0.18)	***
Time Dummy: Fifth Grade	0.63	(0.27)	**	0.25	(0.15)	*	0.68	(0.29)	**
Food and Activity Price and Availability									
Fast Food Price	0.01	(0.02)		0.00	(0.01)		0.01	(0.02)	
Restaurant Price	-0.16	(0.11)		-0.07	(0.03)	**	-0.20	(0.11)	*
# of Limited Service Restaurants	0.16	(0.21)		0.10	(0.05)	**	0.18	(0.23)	
# of Full Service Restaurants	-0.04	(0.14)		-0.05	(0.04)		-0.06	(0.15)	
# of Supermarkets	-1.07	(0.67)		-0.15	(0.14)		-0.99	(0.71)	
# of Convenience Stores	0.86	(0.39)	**	0.11	(0.09)		1.07	(0.42)	***
# of Fitness Centers	0.36	(0.35)		-0.16	(0.08)	**	0.41	(0.37)	
Constant	-2.66	(1.78)		0.56	(0.36)	*	-4.33	(1.91)	**

Table B.3: Coefficients from BMI Equation (by child care mode: informal versus formal)

Variable	Model 1c			Model 2c			Model 3		
No work, use child care (informal or formal)	-2.67	(2.18)		0.00	(2.21)		-3.58	(1.84)	**
Part-time, no child care	-0.23	(0.78)		-1.31	(0.93)		-0.66	(0.75)	
Part-time, informal child care	1.79	(1.58)		-3.17	(1.69)	*	39.67	(1.83)	***
Part-time, formal child care	-2.76	(2.22)		-1.84	(2.42)		1.79	(2.26)	
Full-time, no child care	0.29	(0.81)		-1.60	(1.02)		0.97	(0.86)	
Full-time, informal child care	1.84	(0.95)	**	0.46	(1.19)		2.94	(0.99)	***
Full-time, formal child care	0.05	(1.14)		-2.26	(1.42)		-2.36	(1.25)	*
Current Health	0.83	(0.01)	***	-0.01	(0.01)		0.52	(0.01)	***
Current Health ×									
No work, using child care (formal, informal)	0.04	(0.03)		0.00	(0.03)		0.03	(0.02)	
Part-time, no child care	0.01	(0.01)		0.01	(0.01)		-0.01	(0.01)	
Part-time, using informal child care	-0.01	(0.02)		0.04	(0.02)	*	-0.04	(0.02)	**
Part-time, using formal child care	0.02	(0.03)		0.01	(0.04)		0.02	(0.03)	
Full-time, no child care	0.01	(0.01)		0.01	(0.01)		-0.02	(0.01)	**
Full-time, using informal child care	-0.01	(0.01)		0.00	(0.02)		-0.04	(0.01)	***
Full-time, using formal child care	0.00	(0.02)		0.01	(0.02)		0.01	(0.02)	
Child characteristics									
Male	1.02	(0.23)	***	-			1.20	(0.23)	***
Age	1.08	(1.86)		-4.41	(2.41)	*	-0.95	(1.44)	
Age squared	-0.06	(0.10)		-0.04	0.08		0.06	0.08	
Black	1.46	(0.46)	***	-			1.42	(0.42)	***
Hispanic	0.73	(0.36)	**	-			0.86	(0.32)	***
Siblings	-0.24	(0.11)	**	-0.29	(0.34)		-0.36	(0.11)	***

Table B.3 (continued)

Variable	Model 1c			Model 2c			Model 3		
Mother characteristics									
Age	-0.01	(0.03)		0.11	0.09		-0.03	0.02	
Education									
High School	-0.37	(0.51)		3.29	(1.15)	***	0.27	(0.45)	
Some College	-0.52	(0.52)		4.70	(1.27)	***	-0.06	(0.45)	
≥ College	-1.57	(0.56)	***	5.45	(1.57)	***	-1.38	(0.50)	***
Married	0.67	(0.57)		-0.69	(0.73)		-0.34	(0.47)	
Prior Work	-0.20	(0.30)		-			-0.23	(0.30)	
Father characteristics									
Age	0.01	(0.02)		-0.21	(0.12)	*	0.02	(0.02)	
Education									
High School	-0.93	(0.53)	*	-0.59	(1.05)		-0.27	(0.46)	
Some College	-1.35	(0.54)	**	0.34	(1.14)		-0.94	(0.47)	**
≥ College	-1.79	(0.57)	***	0.82	(1.28)		-1.88	(0.50)	***
Time Dummy: Third Grade	3.06	(0.85)	***	13.52	(3.80)	***	2.31	(0.76)	***
Time Dummy: Fifth Grade	2.57	(1.38)	*	26.19	(7.43)	***	1.47	(1.30)	
Food and Activity Price and Availability									
Fast Food Price	0.15	(0.11)		0.75	(0.40)	*	0.35	(0.10)	***
Restaurant Price	-1.39	(0.54)	***	-6.83	(1.52)	***	-1.19	(0.51)	**
# of Limited Service Restaurants	2.52	(1.09)	**	8.37	(2.24)	***	1.61	(0.98)	*
# of Full Service Restaurants	-1.70	(0.72)	**	-5.59	(2.02)	***	-1.36	(0.64)	**
# of Supermarkets	-8.89	(3.43)	***	-23.52	(6.67)	***	-6.98	(3.09)	**
# of Convenience Stores	5.25	(2.00)	***	8.63	(4.45)	**	6.74	(1.81)	***
# of Fitness Centers	-1.22	(1.78)		-9.76	(3.86)	***	-3.16	(1.55)	**
Constant	9.85	(8.75)		115.63	(17.36)	***	-20.77	(7.21)	***

Table B.4: Coefficients from Reading Scores Equation (by child care mode: informal versus formal)

Variable	Model 1c			Model 2c			Model 3		
No work, use child care (informal or formal)	-1.60	(1.82)		-0.76	(1.86)		0.13	(1.75)	
Part-time, no child care	1.19	(0.68)	*	1.63	(0.78)	**	0.77	(0.74)	
Part-time, informal child care	1.34	(1.17)		1.06	(1.28)		1.53	(1.28)	
Part-time, formal child care	0.35	(1.80)		-3.44	(2.10)	*	-2.37	(1.78)	
Full-time, no child care	-0.48	(0.66)		1.41	(0.80)	*	-1.09	(0.74)	
Full-time, informal child care	-0.55	(0.74)		0.41	(0.90)		-0.52	(0.85)	
Full-time, formal child care	-1.35	(0.95)		-1.49	(1.16)		-3.13	(1.03)	***
Current Health	0.72	(0.01)	***	0.04	(0.01)	***	0.51	(0.01)	***
Current Health ×									
No work, using child care (formal, informal)	0.02	(0.04)		0.01	(0.04)		0.00	(0.03)	
Part-time, no child care	-0.02	(0.01)	*	-0.03	(0.01)		-0.01	(0.01)	
Part-time, using informal child care	-0.03	(0.02)		-0.02	(0.02)		-0.04	(0.02)	*
Part-time, using formal child care	-0.02	(0.03)		0.05	(0.04)		0.02	(0.03)	
Full-time, no child care	0.00	(0.01)		-0.03	(0.02)	*	0.02	(0.01)	
Full-time, using informal child care	0.00	(0.01)		-0.01	(0.02)		0.00	(0.01)	
Full-time, using formal child care	0.02	(0.02)		0.02	(0.02)		0.05	(0.02)	***
Child characteristics									
Male	-0.21	(0.08)	***	-			-0.50	(0.09)	***
Age	0.12	(0.61)		5.98	(0.82)	***	1.57	(0.58)	***
Age squared	0.00	(0.03)		-0.12	(0.03)	***	-0.03	(0.03)	
Black	-1.62	(0.15)	***	-			-2.27	(0.17)	***
Hispanic	-0.39	(0.12)	***	-			-1.03	(0.14)	***
Siblings	-0.19	(0.04)	***	-0.09	(0.12)		-0.31	(0.04)	***

Table B.4 (continued)

Variable	Model 1c			Model 2c			Model 3		
Mother characteristics									
Age	0.02	(0.01)	*	0.03	(0.03)		0.02	(0.01)	**
Education									
High School	0.86	(0.18)	***	0.04	(0.41)		1.15	(0.19)	***
Some College	0.95	(0.18)	***	-0.54	(0.44)		1.47	(0.20)	***
$\geq$ College	2.01	(0.19)	***	-0.38	(0.53)		2.86	(0.21)	***
Married	0.33	(0.19)	*	0.09	(0.25)		0.39	(0.19)	**
Prior Work	0.01	(0.10)		-			0.02	(0.12)	
Father characteristics									
Age	0.00	(0.01)		0.09	(0.04)	**	0.00	(0.01)	
Education									
High School	0.37	(0.18)	**	-0.06	(0.36)		0.54	(0.19)	***
Some College	0.96	(0.19)	***	0.02	(0.39)		1.15	(0.19)	***
$\geq$ College	1.40	(0.19)	***	0.32	(0.43)		1.97	(0.20)	***
Time Dummy: Third Grade	-0.45	(0.28)	*	-8.66	(1.29)	***	-2.23	(0.30)	***
Time Dummy: Fifth Grade	-0.91	(0.46)	**	-16.24	(2.53)	***	-4.15	(0.52)	***
Food and Activity Price and Availability									
Fast Food Price	-0.04	(0.04)		0.26	(0.13)	**	-0.01	(0.04)	
Restaurant Price	0.02	(0.18)		2.74	(0.48)	***	0.14	(0.19)	
# of Limited Service Restaurants	-0.19	(0.36)		0.91	(0.76)		0.79	(0.38)	**
# of Full Service Restaurants	-0.53	(0.23)	**	-1.36	(0.70)	**	-0.80	(0.26)	***
# of Supermarkets	3.30	(1.12)	***	4.31	(2.21)	**	3.08	(1.19)	***
# of Convenience Stores	-1.34	(0.65)	**	-0.25	(1.51)		-3.15	(0.71)	***
# of Fitness Centers	1.40	(0.56)	***	2.74	(1.30)	***	2.02	(0.60)	***
Constant	12.04	(2.89)	***	-1.76	(5.85)		-3.40	(2.92)	

Table B.5: Coefficients from Math Scores Equation (by child care mode: informal versus formal)

Variable	Model 1c			Model 2c			Model 3		
No work, use child care (informal or formal)	1.46	(1.63)		1.91	(1.58)		2.22	(1.59)	
Part-time, no child care	1.73	(0.64)	***	1.71	(0.72)	**	1.14	(0.71)	*
Part-time, informal child care	1.31	(1.10)		0.76	(1.15)		1.19	(1.20)	
Part-time, formal child care	6.03	(1.80)	***	5.64	(1.86)	***	3.34	(1.80)	*
Full-time, no child care	-0.32	(0.63)		1.10	(0.76)		-0.63	(0.73)	
Full-time, informal child care	1.46	(0.70)	**	1.50	(0.84)	*	1.58	(0.82)	**
Full-time, formal child care	-0.34	(0.92)		0.02	(1.08)		-2.14	(1.00)	**
Current Health	0.78	(0.01)	***	-0.07	(0.01)	***	0.51	(0.01)	***
Current Health ×									
No work, using child care (formal, informal)	-0.04	(0.03)		-0.03	(0.03)		-0.04	(0.03)	
Part-time, no child care	-0.03	(0.01)	***	-0.03	(0.01)	**	-0.02	(0.01)	
Part-time, using informal child care	-0.02	(0.02)		-0.01	(0.02)		-0.02	(0.02)	
Part-time, using formal child care	-0.11	(0.03)	***	-0.10	(0.03)	***	-0.07	(0.03)	**
Full-time, no child care	0.00	(0.01)		-0.02	(0.01)		0.01	(0.01)	
Full-time, using informal child care	-0.03	(0.01)	**	-0.03	(0.02)	*	-0.03	(0.01)	**
Full-time, using formal child care	0.00	(0.02)		0.00	(0.02)		0.03	(0.02)	**
Child characteristics									
Male	0.77	(0.07)	***	-			1.05	(0.09)	***
Age	0.54	(0.59)		12.46	(0.75)	***	3.59	(0.56)	***
Age squared	-0.05	(0.03)		-0.37	(0.02)	***	-0.14	(0.03)	***
Black	-1.58	(0.14)	***	-			-2.85	(0.17)	***
Hispanic	-0.24	(0.11)	**	-			-1.05	(0.14)	***
Siblings	-0.08	(0.04)	**	0.15	(0.10)		-0.13	(0.04)	***

Table B.5 (continued)

Variable	Model 1c			Model 2c			Model 3		
Mother characteristics									
Age	0.00	(0.01)		-0.01	(0.03)		0.01	(0.01)	
Education									
High School	0.62	(0.17)	***	0.68	(0.37)	*	1.07	(0.19)	***
Some College	0.78	(0.17)	***	0.64	(0.40)		1.51	(0.20)	***
$\geq$ College	1.55	(0.18)	***	0.41	(0.48)		2.81	(0.21)	***
Married	0.38	(0.18)	**	0.16	(0.22)		0.42	(0.18)	**
Prior Work	-0.10	(0.09)		-			-0.07	(0.12)	
Father characteristics									
Age	0.02	(0.01)	**	0.14	(0.04)	***	0.03	(0.01)	***
Education									
High School	-0.18	(0.17)		-0.17	(0.32)		-0.10	(0.19)	
Some College	0.19	(0.18)		-0.62	(0.35)	*	0.32	(0.19)	*
$\geq$ College	0.61	(0.18)	***	-0.15	(0.39)		1.15	(0.20)	***
Time Dummy: Third Grade	0.73	(0.27)	***	-13.37	(1.17)	***	-2.40	(0.32)	***
Time Dummy: Fifth Grade	1.59	(0.44)	***	-23.41	(2.29)	***	-3.69	(0.55)	***
Food and Activity Price and Availability									
Fast Food Price	0.00	(0.04)		0.43	(0.12)	***	-0.02	(0.04)	
Restaurant Price	-0.08	(0.17)		1.88	(0.44)	***	-0.14	(0.19)	
# of Limited Service Restaurants	-0.14	(0.34)		0.79	(0.69)		0.64	(0.38)	*
# of Full Service Restaurants	-0.11	(0.22)		-1.53	(0.63)	**	-0.43	(0.27)	*
# of Supermarkets	2.01	(1.07)	*	3.16	(2.00)		2.43	(1.18)	**
# of Convenience Stores	-0.97	(0.62)	*	1.69	(1.36)		-2.99	(0.72)	***
# of Fitness Centers	0.75	(0.53)		3.73	(1.17)	***	0.52	(0.60)	
Constant	8.23	(2.76)	***	-29.00	(5.29)	***	-12.52	(2.83)	***

Appendix to Chapter 3

C.1 Empirical Estimation using the Conditional Density Estimation

The following steps were taken to implement the Conditional Density Estimation technique.

1. **Interval numbers**

   Ten intervals were chosen for this paper (K=10). The first interval therefore represents the 10th percentile of the z-score outcome, the second interval the 20th percentile, and so on. The number of intervals was chosen to maximize the goodness of fit of the model. A description of how log-likelihood functions were compared can be found in Gilleskie and Mroz (2004).

2. **Evaluation of outcome in each cell**

   A simple arithmetic mean of each cell was used as the expectation of the outcome in each cell. Specifically, given that the interest is in evaluating the impact of a variable x on the expected value of a function $g(B)$, where

   $$\frac{\partial E(g(B)|x)}{\partial x} = \sum_{k=1}^{K} g^*(k|K) \left\{ \frac{\partial \lambda(k,x) \prod_{j=1}^{k-1} [1 - \lambda(j,x)]}{\partial x} \right\} \tag{C.1}$$

   I evaluate $g^*(k|K)$ as

   $$g^*(k|K) = \frac{\sum_{b \in [b_{k-1}, b_k)} g(b)}{\sum_{b \in [b_{k-1}, b_k)} 1} \tag{C.2}$$

3. **Approximation of the density**

   The conditional density function $\Pr[b_{k-1} \leq B < b_k|x]$ is approximated using a logit function for the probability that an outcome falls in the kth interval, conditional on it not having fallen in the last $k-1$ intervals. A separate logit function can be evaluated for each hazard in a given interval, however the logit probability is estimated using interval numbers, covariates, and the interaction of the covariates and interval numbers as controls.

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