A Dynamic Model of the Effects of Child Care and Maternal Employment Choices on Children’s Body Weight

Mai N. Hubbard
Department of Economics
University of North Carolina at Chapel Hill

Preliminary and Incomplete
October 29, 2007

Abstract

The rapid increase in the prevalence of childhood obesity in the United States has alarmed researchers who have increasingly sought to identify the cause of this public health problem. Despite a large number of potential explanations for the rise in obesity rates, the research to date has been methodological diverse with no clear consensus on the cause. This has greatly complicated and hindered the implementation of programs and policies aimed at reducing childhood obesity. In this paper, I add to the current research by examining two potential contributors to the rise in childhood obesity: maternal employment and after school child care usage. Specifically, I estimate the effects of time spent in child care and a mother’s hours of employment on childhood obesity using data from the Early Childhood Longitudinal Study Kindergarten Class of 1998-1999. I also address a potential self-selection problem by jointly estimating the child care and employment equations with the child’s health production function using an unobserved factors model that controls for unobserved heterogeneity. Preliminary findings where I do not control for endogeneity indicate that the impact of child care and maternal employment on the probability of being obese is positive and significant.
1 Introduction

The rapid increase in obesity\textsuperscript{1} prevalence over the past several decades has raised grave concerns among researchers, policy-makers and the general public. Results from national health examination surveys conducted between the mid-1970s to the start of the 21st century show prevalences of both adult and childhood obesity increasing at alarming rates. The number of obese adults (ages 20 to 74) in the United States, for instance, increased from around 15 to roughly 30 percent while for young adults (ages 12 to 19) the rate more than tripled from around 5 to 17 percent during this time period (Centers for Disease Control and Prevention, 2007). As a result, biomedical researchers and social scientists have made an aggressive push to find an explanation for this national health epidemic. Despite a large number of studies however, a consensus on what may have caused the acceleration in obesity prevalence has yet to be established. Furthermore, the problem shows no signs of abating. The Centers for Disease Control and Prevention (CDC), for example, stated that the “although one of the national health objectives for the year 2010 is to reduce the prevalence of obesity among adults to less than 15%, current data indicate that the situation is worsening rather than improving.”.

What is clear is that obesity is a direct consequence of consuming more calories than are expended over time. Therefore, current explanations for the rise in obesity prevalence have involved changes to either dietary or activity behavior that have occurred over the past several decades. Increases in junk food and restaurant foods, in soda consumption and other beverages that are high in sugars, and in the consumption of pre-cooked meals at home that are often laden with fats are frequently cited as explanations for the increase in caloric intake. Reasons for the decline in caloric expenditure include decreases in physical activity during school (for children) and at work (for adults) and increases in the time spent in sedentary activities such as television viewing, using the computer, and playing video games. Although a large biomedical literature on the relationship between such factors and obesity exists, much of the research, to date, has failed to estimate causal effects as a result of omitted variable bias. Furthermore, the majority of studies by economists

\textsuperscript{1}Obesity and overweight are currently determined using a standardized measure called Body Mass Index (BMI). BMI simply estimates a ratio of weight in kilograms to height in meters squared. Adults(greater than 20 years of age) are considered overweight if their BMI is between 25 and 30, obese if between 30 and 35, and morbidly obese if BMI is greater than 35. Children’s (ages 2-20) obesity status is determined using growth charts developed by the Centers for Disease Control. Children are classified as overweight if their BMI is between the 85th and 95th percentile, and obese if greater than the 95th percentile for their sex and age.
(to my knowledge) have focused 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 built-environment that may encourage behaviors that increase body mass because they do not have the ability nor the capacity to make informed health choices.

Although an agreement on the cause of the rise in obesity prevalence has yet to be reached, researchers, on some level, all agree that the immediate and long term implications of childhood obesity on physical and emotional well-being are severe. Children who are obese suffer from a multitude of physical ailments including heart disease, Type II diabetes, sleep apnea, orthopedic conditions, and asthma (Brookings Institute, 2006). Chronic illnesses (e.g. heart disease and Type II diabetes) can require long term management of the disease and can, as a result, reduce individuals’ quality of life. Furthermore, children who are obese often suffer from low self-esteem and psychological trauma as a result of teasing and bullying from their peers.

Problems related to childhood obesity extend beyond the medical and physical and can cause significant economic burden to individuals, families, and society. Treatment of individuals with lifelong illnesses can be costly, especially if its onset is from an early age. Moreover, disability payments can increase substantially if these illnesses result in physical disabilities from an earlier age. On the individual level, Cawley (2004) has found weight to have lowering effects on the wage rates of white females. If Whitaker et al.’s (1997) results that overweight children (compared to children of normal weight) have a higher probability of being obese when adults is correct, then the long term consequences of being overweight as a child may not only be debilitating physically but also through future wage returns.

In this paper, I add to the current research on childhood obesity by examining the effects of two notable changes that occurred during the same period in which childhood obesity prevalence increased: an increase in maternal employment and in after school child care usage (most likely due to an expansion of women into the labor force). Both of these inputs can affect a child’s risk of becoming obese through various mechanisms. For example, employed mothers may have less time to spend preparing meals and may substitute home cooked meals with fast foods and restaurant meals which are often rich in fats and calories. They may also be unable to directly monitor the daily activities of their children who may then choose to spend more time in sedentary activites. And because working mothers are unable to spend all of their time with their children, they are
more likely to participate in informal (defined as care provided by relatives or a child’s older sibling) or formal (defined as paid care) after school child care. Within child care settings, both informal and formal child care workers may be less attentive to the health needs of each individual child, thereby increasing the risk of overweight. On the other hand, children in formal child care may engage in a greater number of physical activities with other children and eat healthier foods if the after school child care program adheres to a regimented eating and activity schedule. In spite of the potential linkages between maternal employment, child care, and obesity this subject matter has received surprisingly little research attention.

In estimating maternal employment and child care usage on child health, I am faced with a potential endogeneity problem resulting from two sources. First, women who use after school care or work may not be a random subset of mothers. In effect, there may be unobservable characteristics of the mother or child that may influence the choice to use child care or to work. To account for this problem, I directly model child care usage and maternal employment using State child care and welfare laws, and labor market conditions as instrumental variables. The second source of endogeneity bias results from a simultaneity bias in which mothers’ employment and child care choices may be determined by the health status of their children. I address this problem of reverse causality by estimating a dynamic model that accounts for the sequential decision making behavior of the mother where child health in the previous period influences employment and child care choices. My estimation strategy will then be to jointly estimate a dynamic model of maternal employment, child care, and child health using an unobserved effects model that controls for unobserved heterogeneity. These results are compared to estimates derived from other estimational techniques including probit and bivariate probit estimation.

This paper is organized as follows. In Section 2 I review the current literature. The theoretical and empirical models are discussed in Sections 3 and 4, respectively. In Section 5, I describe the data and in Section 6 I provide estimation results. Section 7 concludes with a description of my research agenda.
2 Literature Review

In this section I present an extensive overview of the current economics literature on obesity. I begin with research that focuses primarily on adult obesity, then review works focusing on childhood obesity. Lastly, I discuss some papers written about the consequences of obesity. Although a large biomedical literature has examined the causes of obesity, I do not discuss the papers here.

2.1 Potential Causes of Adult Obesity

Research examining the causes of adult obesity has increased greatly in the past decade within the economics profession. One of the most oft-cited explanations for the rise in obesity prevalence among Americans is technological change which Philipson and Posner (1999), Lakdawalla and Philipson (2002), and Cutler and Shapiro (2003) all refer to in their papers. Philipson and Posner (1999) and Lakdawalla and Philipson (2002) suggest that obesity is a result of shifts in society from an agriculturally intensive workforce to that of a more sedentary nature which ultimately led to a decline in daily caloric expenditure. Using data from the National Health Interview Survey and National Longitudinal Survey of Youth (1979), Lakdawalla and Philipson (2002) show strenuousness of occupation to have an inverse relationship with BMI (as job strenuousness declines, BMI increases). Cutler and Shapiro (2003) on the other hand argue that changes in technology led to cheaper and faster production of foods that allowed Americans to enjoy more food for less money (resulting in an increase in caloric intake).

Another line of obesity research that has received a great deal of attention recently is the causal role of smoking on rising obesity rates (Chou et al., 2004; Gruber and Frakes, 2005; Rashad, 2004; Eisenberg, 2006). Cutler et al. (2003) and Chou et al. (2003) both use data from the Behavioral Risk Factor Surveillance System (BRFSS) and find contradictory results. On one end, Chou et al. (2004) show smoking prices to have a positive relationship with obesity risk (as cigarette prices increase, demand decreases, and obesity rates increase). On the other, Gruber and Frakes (2005) argue that a weakness of Chou et al.’s (2003) analysis is the use of endogenous cigarette prices and find that by using cigarette taxes and controlling for fixed time effects, smoking has a negative effect on BMI. Their analysis, nevertheless, finds the smoking price elasticites to be much smaller than the typical range of elasticities and therefore their estimates are suspect. Furthermore, their
findings that smoking actually increases BMI counters much of the biomedical literature which finds smoking to negatively affect BMI through, for example, appetite suppression.

2.2 Potential Causes of Child Obesity

Although the literature focusing on adult obesity can in some ways explain the rising prevalence of child obesity, determinants of the latter can potentially differ from adults because children are unable to control the environment in which they live and are also unable to make informed choices regarding their own health. As a result, the available research often examines the impact of societal and environmental changes, and changes in parental behavior on childhood obesity.

The impact of changes in parental behavior, in particular the effect of maternal employment on childhood overweight (Fertig, 2006; Anderson et al., 2002) has recently received a fair deal of attention. Fertig (2006) estimates the impact of employment on the time allocated to activities by children and their food intake, and then estimates the effect of these inputs on the child’s BMI. Her analysis involves estimating the two equations using a seemingly unrelated regression technique and she finds that maternal employment increases time spent viewing television and decreases the number of home cooked meals. She also finds that these two inputs positively impact children’s BMI. Her results, however indicate that maternal employment had an economically insignificant influence on childhood overweight. Estimates from her paper may be subject to bias however, because mothers who are more likely to work or allow her child to engage in certain activities may also have unobserved traits that influence the health of the child. Her failure to control for this problem can result in biased estimates of the effect of maternal employment on child health.

A working paper by Wilson (2004) provides an overview of the recent research done in the area of child obesity and also provides insight into what may have led to this emerging trend of childhood overweight using several different datasets (including the Panel Study of Income Dynamics (PSID) child supplement, National Longitudinal Survey of Youth (NLSY) and National Health Expenditures Survey (NHES)). Through his analysis, he finds that dietary inputs and labor market allocations cannot be the driving force behind childhood obesity. Furthermore, he shows that time allocation of children in activities to be important determinants of BMI, but unable to explain the trends observed in the recent rise in childhood overweight.

In a simple example, suppose that the author models childhood obesity ($O_i$) as a function of number of hours of maternal employment ($H_i$) and exogenous variables ($X_i$):

\[ O_i = \beta_0 + \beta_1 \cdot H_i + \beta_2 \cdot X_i + \epsilon_i \]

Taking expectations:

\[ E(O_i|H_i, X_i) = \beta_0 + \beta_1 \cdot H_i + \beta_2 \cdot X_i + E(\epsilon_i|H_i, X_i) \]

\[ = \beta_0 + \beta_1 \cdot H_i + \beta_2 \cdot X_i \]

The term above shows that if the error term ($\epsilon_i$) is uncorrelated with the explanatory variables then $\beta_1$ measures the
To control for such unobserved heterogeneity, Anderson et al. (2002) estimate the effect of maternal employment on child overweight using several estimation techniques. Using data from the National Longitudinal Survey of Youth (NLSY) the authors first exploit the longitudinal nature of their data and estimate the effect using a fixed effects approach. The authors find a positive relationship but there are several problems with using the fixed effects model. The first is that the unobserved heterogeneity component must be time invariant and this can be a strong assumption to make. Second, there is a large loss in the degrees of freedom when using the fixed effects or a within estimation approach. Lastly, the method can exacerbate attenuation bias due to measurement error.

Using a method that does not involve fixed effects, the authors also apply an instrumental variables technique to estimate the effect. Using State labor market conditions, welfare benefit levels, child care laws, and child care worker wages as instruments, the authors find similar results to those using the fixed effects approach however, the impact is statistically insignificant. In effect, estimates of the impact of maternal employment on childhood obesity are still mixed and very little convincing results have yet to be presented in this area of work.

Several papers have examined environmental effects on childhood obesity such as food processing (MacInnis and Rauser, 2005), fast food restaurant advertising (Chou et al., 2005), and State regulations and laws. MacInnis and Rauser (2005), who estimate the effect of processed foods on obesity, find that the increase in consumption of high density foods (measured by the number of calories per gram) has led to an overwhelming increase in obese children even after controlling for total caloric intake. Their estimation approach involves regressing obesity on food density controlling fixed effects. Again, their work is limited because they employ a fixed effects estimation approach in which they place a strong assumption that the unobserved heterogeneity component is time invariant. In the study examining the effects of fast food advertising on obesity by Chou et al. (2005), the authors describe several mechanisms by which fast food advertising on television can result in the childhood overweight including an increase in the caloric intake of junk foods and a greater overall consumption of foods while viewing these ads. Using both a fixed effects and instrumental variables approach to estimate the effect they find a positive, albeit weak, relationship.

change in obesity caused by a ceteris paribus change in maternal employment hours. However, if there is a failure to include an explanatory variable that is correlated with both the explanatory variable and the outcome of interest, $\beta_1$ fails to capture the effect of a change in employment on obesity. The parameter is obscured by the correlation between the unobserved error and explanatory variable and therefore the estimate of the parameter will capture not only the effect of maternal employment on obesity but also the effect of the unobserved variable as well.
The effect of State regulations on obesity have also been examined. Cawley et al. (2005) examine the effect of State physical education requirements on overweight. They use an instrumental variables approach and use several state regulations on physical education programs to control for the endogeneity of time spent in physical activity. They find that regulations on the time spent in physical education classes has a positive effect on time spent exercising but very little effect on obesity. Frisvold (2006) studies the effect of Head Start participation on childhood overweight. Head Start programs provide a wide array of services to poor and disabled children including nutritional services. The authors estimate an average treatment effect on the treated using an instrumental variables approach. He finds that Head Start significantly reduces the probability of becoming overweight or obese in later childhood if the participant was black, however the same effect could not be found for whites.

2.3 Immediate and Future Consequences of Obesity

The importance of examining the impact of various determinants on obesity are highlighted by the detrimental effects that obesity can have on individuals both physically and economically. For example, many studies in the biomedical literature suggest that obesity has a strong relationship with numerous illnesses such as Type II diabetes, high blood pressure, and cardiovascular illnesses. With the rising prevalence of obese children these physical ailments, once thought to be debilitating illnesses suffered only by adults, have started to appear in children. As a result, it has become crucial that researchers find an explanation for the sudden increase in childhood obesity.

Beyond the physical and psychological consequences, obesity has a large impact economically. For example, Cawley (2004) estimates the effect of obesity on wages using the NLSY. Although his study does not directly examine the impact of child obesity on wages studies\(^4\) have shown a positive relationship between childhood and adult obesity and thus Cawley’s work suggests that children who are obese are more likely to have lower wages as adults. In his study, he estimates the effect of BMI on wages using a fixed effects and instrumental variables (IV) approach. His IV results indicate that weight does seem to lower wages for white females. Although the mechanisms of this effect are not clearly understood, the author cites two possible explanations of why wages

\(^4\)MacInnis and Rausser (2005) report that half of children reporting to be obese/overweight also report being overweight/obese as adults.
may be reduced: (1) a decrease in productivity for overweight women; (2) discrimination against overweight/obese individuals.

3 Theoretical Motivation

In this section I develop and describe a theoretical model that should motive the empirical specification outlined in the following section \(^5\). The model presented is consistent with Grossman’s (1972) human capital framework where individuals do not derive utility from medical inputs per se, but rather through better health which is produced through health inputs. To give a rather simple example, preventative care and visits to the hospital can enhance the health of an individual. Thus, consumers demand these health inputs, not because they derive utility directly from these goods but because they demand good health. To briefly summarize Grossman’s model, individuals are born with a stock of health which depreciates over time. In each period \(t\), individuals invest in their health using their own time, health inputs, and market goods and services. One of the key assumptions of this model is that individuals can choose their length of life and will at some point die if their health stock falls below a certain threshold.

In my model, the mother derives utility in period \(t\) from the health of her child, leisure, and consumption of commodity goods. Health (or obesity in particular) of the child is then determined by lifestyle behaviors, maternal employment, and child care choices. In previous studies, a static framework has been used to examine the effect of maternal employment on obesity (Fertig, 2006; Anderson, 2002). This framework assumes that the mother’s decisions at time \(t\) do not affect utility at time \(t + 1\) and furthermore, that her decision making behavior is not influenced by the status of her child’s health despite the possibility of such a relationship. Therefore I use a dynamic framework in this paper to capture the sequential decision making behavior of mothers. The specific timing of the events can be described as follows:

1. At time \(t\) the mother observes the health outcome of her child (e.g. where or not her child is obese)

2. Given her observation, she will decide on how much to work and to use child care.

\(^5\)It should be noted that this paper does not attempt to estimate the underlying preference parameters.
3. At time $t + 1$ the child’s health status will be realized and this will depend on child care and maternal employment choices made at time $t$.

To begin, suppose that at the beginning of each period $t$, the mother observes the health of her child and after doing so chooses between three types of employment:

$$h_{it} = \begin{cases} 
1 & \text{If not working} \\
2 & \text{If } >0 \text{ and } \leq 20 \text{ hours per week} \\
3 & \text{If } \geq 20 
\end{cases}$$

where an indicator $H^h_{it} = 1$ if employment of type $h$ is chosen and $\sum_{h=1}^{3} H^h_{it} = 1$. The individual also chooses among three types of after school child care:

$$c_{it} = \begin{cases} 
1 & \text{If not using child care} \\
2 & \text{If } >10 \text{ and } \leq 20 \text{ hours per week} \\
3 & \text{If } >20 \text{ and } \leq 30 \text{ hours per week} \\
4 & \text{If } >30 \text{ hours per week}
\end{cases}$$

where for an individual $i$, $C^c_{it} = 1$ if child care alternative $c$ is chosen and $\sum_{c=1}^{3} C^c_{it} = 1$.

The individual’s current period utility is a function of her consumption ($X_{it}$), leisure time ($L_{it}$), health (obesity status ($O_{it}$)) of her child, and a preference error term ($\epsilon^u_{it}$) and can be expressed as the following:

$$U_{it} = U(X_{it}, L_{it}, O_{it}; \epsilon^u_{it})$$

Health of the child in period $t + 1$ is a function of current health ($O_{it}$) as well as the child’s energy balance in period $t$. The child’s energy balance is a function of his caloric intake ($I_{it}$) and caloric expenditure ($E_{it}$). The probability that the individual is overweight in period $t + 1$ can then be written as:

$$Pr(O_{it+1} = 1) = f(O_{it}, I_{it} - E_{it}; W_{it})$$
Observable characteristics of the mom and child that can influence the way in which energy intake and expenditure are converted into body mass in future periods are included in the vector $W_{it}$. This vector includes characteristics such as child’s age, race, and genetic information, gender, and the mother’s health status and her caloric intake and expenditure.

Inputs chosen in the current period by the mother can influence child overweight in future periods through both caloric intake and expenditures. Child care usage, for example, can increase the caloric intake of children because child care workers may not be as sensitive to the quality of the food given to the child compared to the parent. Furthermore, they may give children foods that are easier to prepare (processed foods) as well as foods that are not as perishable (canned fruits instead of raw). On the other hand, children in child care settings may be more active because of the play time with other children which would increase caloric expenditure. The mother’s time spent at work can also affect child overweight through both caloric intake and expenditures—mothers that work full time may have less time to prepare healthy meals resulting in an increase in caloric intake and have less time engaging directly with the child in healthy activities that can lead to a decline in caloric expenditure. Individuals therefore invest in child health according to the following production functions:

$$I_{it} = I(c_{it}, h_{it}, F_{it})$$
$$E_{it} = E(c_{it}, h_{it}, A_{it}^P, A_{it}^R)$$

Caloric intake ($I_{it}$) is a function of child care use ($c_{it}$), maternal employment ($h_{it}$) and a vector $F_{it}$ of food intake that includes variables such as sweets, junk food and vegetable consumption. Caloric expenditure ($E_{it}$) is also a function of child care and maternal employment as well as a vector of passive activities ($A_{it}^P$) and rigorous activities ($A_{it}^R$). $A_{it}^P$ includes activities such as playing computer games, watching televisions, and surfing the web and $A_{it}^R$ include variables such as playing sports, doing homework, and playing musical instruments.
The mother is constrained by time (which is normalized to 1):

\[
\sum_{h=2}^{3} T_{ht} \cdot H_{ht} + L_{it} = 1
\]

(6)

where \(T_{it}\) is the time she spends at work and allocates her income between consumption goods \((X_{it})\), child care \((C_{it})\) and a vector \(D_{it}\) that includes the cost of food and engaging in activities:

\[
X_{it} + \sum_{c=1}^{4} a_{it} \cdot C_{ic} + \sum_{d=1}^{m} p_{id} \cdot D_{id}^{d} = \sum_{h=2}^{3} Y_{ih} \cdot H_{ih} + N_{it}
\]

(7)

where \(a_{it}\) is the price of after school care, and \(p_{id}^{d}\) is a vector of prices corresponding to goods in vector \(D_{it}\). The mother is constrained by her income \((Y_{it})\) which depends on whether she is working full or part time and a vector of non-wage income \((N_{it})\) which includes her husband’s income, benefits and assets.

Thus, the mother faces the following optimization problem:

\[
\max \ E_{it} \sum_{t=0}^{T} \beta^{t} \cdot U(X_{it}, L_{it}, O_{it}; \epsilon_{it}) \quad \text{s.t.}
\]

\[
Pr(O_{it+1} = 1) = f(O_{it}, I_{it} - E_{it}; W_{it})
\]

\[
I_{it} = I(c_{it}, h_{it}, F_{it})
\]

\[
E_{it} = E(c_{it}, h_{it}, A_{it}^{P}, A_{it}^{R})
\]

\[
\sum_{h=2}^{3} T_{ht} \cdot H_{ht} + L_{it} = 1
\]

\[
X_{it} + \sum_{c=1}^{4} a_{it} \cdot C_{it} + \sum_{d=1}^{m} p_{it}^{d} \cdot D_{it}^{d} = \sum_{h=2}^{3} Y_{ih} \cdot H_{ih} + N_{it}
\]

(8)

This maximization problem can be rewritten as a Bellman equation and the lifetime value of a particular employment and child care alterative \(h\) and \(cc\) at time period \(t\) can be expressed as:
where $\beta$ is a discount factor, $R_{it}$ is a vector of exogenous prices, and

$$V(O_{it+1}, W_{it+1}, R_{it+1}) = E_t[\max_{h \in H, c \in cc} V_{hcc}(O_{it+1}, W_{it+1}, R_{it+1}, \epsilon_{it+1})]$$

(10)

is the expectation of the maximum lifetime value at time $t + 1$. The maximal expected value of lifetime utility can be written as:

$$V(O_{it}, W_{it}, R_{it}) = E_{t-1}[\max_{h \in H, c \in cc} V_{hcc}(O_{it}, W_{it}, R_{it}, \epsilon_{it})]$$

(11)

A detailed description of the derivation of the Bellman equation can be found in Appendix B.

4 Empirical Model

I use three approaches to estimate the impact of maternal employment and child care usage on childhood overweight. To begin, I model a child’s obesity status, maternal employment, and child care usage as:

$$O_{it+1}^* = \beta_0 + \beta_1 \cdot O_{it} + \sum_{c=2}^{4} \beta_c^2 \cdot C_{it}^c + \sum_{h=2}^{3} \beta_h^h \cdot H_{it}^h + \beta_4 \cdot W_{it} + \epsilon_{it}$$

$$O_{it+1} = \begin{cases} 1 & \text{If Obese} \\ 0 & \text{Otherwise} \end{cases}$$

(12)
\[
V_{it}^c = \delta_0^c + \delta_1^c \cdot O_{it} + \delta_2^c \cdot W_{it} + \delta_3^c \cdot R_{it} + \eta_{it}^c \quad c = 1, 2, 3, 4
\]

\[
C_{it}^c = \begin{cases} 
1 & \text{If } V_{it}^c > V_{it}^{c'} \forall c \neq c' \in [1, 2, 3, 4] \\
0 & \text{Otherwise}
\end{cases}
\]

(13)

\[
V_{it}^h = \delta_0^h + \delta_1^h \cdot O_{it} + \delta_2^h \cdot W_{it} + \delta_3^h \cdot R_{it} + \eta_{it}^h \quad h = 1, 2, 3
\]

\[
H_{it}^h = \begin{cases} 
1 & \text{If } V_{it}^h > V_{it}^{h'} \forall h \neq h' \in [1, 2, 3] \\
0 & \text{Otherwise}
\end{cases}
\]

(14)

The decision to use child care of type \(c\) and to engage in employment of type \(h\)\(^6\) for a child \(i\) at time \(t\) depends on the obesity status in the last period \((O_{it})\), observable characteristics \((W_{it})\) that can influence the way in which caloric intake and expenditures are converted into body mass (e.g., gender, race, age, mother’s education, etc.) and \(R_{it}\), a vector of exclusion restrictions. A list and description of the exogenous variables are available in Table 1 in Appendix A and a list of the exclusion restrictions are available in Table 2. The mother chooses child care of type \(c\) if the indirect utility from doing so is greater than is she were to choose any other type of child care: \(V^c > V^{c'} \forall c \neq c' \in [1, 2, 3, 4]\) The same is true for maternal employment choices: the mother will choose employment of type \(h\) as long as her indirect utility from doing so exceeds the utility she would receive from choosing any other employment type.

The child’s health production function is modeled as a function of obesity status in the previous period \((O_{it})\), indicators for child care \((C_{it}^c)\) which are equal to one if child care of type \(c\) is chosen, maternal employment indicators \((H_{it}^h)\) which are equal to one if employment of type \(h\) is chosen, and exogenous variables \((W_{it})\). The outcome is a binary indicator where \(O_{it+1} = 1\) if the child is obese (BMI is greater than the 95th percentile for age and sex).

\(^6\) As described in the theoretical section, the mother can choose from four types of child care: \(C_{it}^1 = 1\) if she does not use child care, \(C_{it}^2 = 1\) if she chooses to use between zero and ten hours of child care per week, \(C_{it}^3 = 1\) if between ten and twenty hours of child care are used per week, and \(C_{it}^4 = 1\) if more than thirty hours of child care are used per week. She also chooses from three types of employment modes: \(H_{it}^1 = 1\) if she chooses not to work, \(H_{it}^2 = 1\) if she chooses to work between zero and twenty hours per week, and \(H_{it}^3 = 1\) if she chooses to work more than twenty hours per week.
The estimation approach I take to measure the coefficients of interest depends on what assumptions I place on the error terms: $\epsilon_{it}$, $\eta_{c_{it}}$, and $\eta_{h_{it}}$. If I assume that the correlation between the error terms are equal to zero or $\forall h = 1, 2, 3$ and $\forall c = 1, 2, 3, 4$:

$$E(\epsilon_{it}|O_{it}, C_{c_{it}}, H_{h_{it}}, W_{it}) = 0$$

(15)

then the three equations (equations 12, 13, and 14) can be estimated independently. If I then assume that $\epsilon_{ijt}$ is standard normally distributed, the likelihood function can be written as

$$L = \prod_{i=1}^{N} \prod_{t=1}^{T} \Phi(\gamma)_{O_{it}} \cdot (1 - \Phi(\gamma))^{1-O_{it}}$$

(16)

where $\gamma = \beta_0 + \beta_1 \cdot O_{it} + \sum_{c=2}^{4} \beta_2 \cdot C_{c_{it}} + \sum_{h=2}^{3} \beta_3 \cdot H_{h_{it}} + \beta_4 \cdot W_{it}$ and $\Phi(\cdot)$ represents the standard normal cumulative distribution function. The parameters in the model can then be estimated by maximizing the likelihood function with respect to the unknown parameters of the model.

Independence of the error terms implies that the explanatory variables in the health production function are exogenous. That is, there are no unobservable factors that are correlated with the explanatory variables that also affects the health outcome. This assumption however, may potentially not hold because mothers who are more likely to work or to use child care may have unobservable traits that also affects the child’s health. A specific example would be a mother’s physical disability, which is unobserved in my data set. If a mother has a disability that limits the number of hours she works and also reduces her ability to properly care for her child’s health, then the estimate that I obtain by simply regressing obesity on maternal employment will be biased and confounded with the effect of the mother’s disability.\footnote{Econometrically, suppose that I am estimating the following regression

$$Y = \beta_0 + \beta_1 \cdot X + \beta_2 \cdot W + \gamma \cdot r + \epsilon$$

where $X$ and $W$ are explanatory variables, $r$ is an unobserved variable that affects the outcome $Y$ and is correlated with $X$ and $\epsilon$ is an idiosyncratic error term. Consequently,}
(equation 12) will result in biased estimates of the coefficients (if maternal employment and child care usage are endogenous) unless I control for the unobservable heterogeneity.

I use two econometric approaches to address the potential problem of unobservable heterogeneity. The first approach assumes that the error terms are joint normally distributed and estimates the parameters using a full information maximum likelihood approach. The second relaxes the distributional assumption and approximates a discrete distribution for the unobservable heterogeneity components. The two approaches are discussed in further detail below.

4.1 Full Information Maximum Likelihood Estimator under Joint Normality

To estimate the model using a full information likelihood approach I first assume that the error terms a joint normally distributed. I can then write the likelihood function as:

\[
L = \prod_{c=1}^{4} \prod_{h=1}^{3} \prod_{a_1=0}^{1} \prod_{a_2=0}^{1} \prod_{a_3=0}^{1} Pr(O_{it} = a_1, C_{it}^c = a_2, H_{it}^h = a_3)
\]

where \( Pr(O_{it} = a_1, C_{it}^c = a_2, H_{it}^h = a_3) \) is the probability that an individual \( i \)'s indicators for obesity, child care and employment at time \( t \) are equal to \( a_1, a_2, \) and \( a_3 \), respectively, where \( a_1, a_2, \) and \( a_3 \) take values of either zero or one. I then maximize the likelihood function with respect to the unknown parameters of the model.

\[
r = \delta_0 + \delta_1 \cdot X + \eta
\]

where \( \eta \) is uncorrelated with the explanatory variables. If I insert the above equation into the original linear equation of interest and rearrange variables, I obtain:

\[
Y = (\beta_0 + \gamma \cdot \delta_0) + (\beta_1 + \gamma \cdot \delta_1) \cdot X + \beta_2 \cdot W + (\gamma \cdot \eta + \epsilon)
\]

If I take the plim of \( \hat{\beta}_1 \) then

\[
plim \hat{\beta}_1 = \beta_1 + \gamma \cdot \delta_1 = \beta_1 + \gamma \cdot \frac{cov(X, r)}{var(X)}
\]

As a result, if the unobserved heterogeneity term has a positive effect on both the explanatory variable and outcome of interest, the estimate of the effect of \( X \) on \( Y \), \( \hat{\beta}_1 \), will be overbiased since

\[
plim \hat{\beta}_1 > \beta_1
\]
4.2 Discrete Factor Approximation Approach

The second estimation approach that I use relaxes the joint normality assumption by estimating the distribution of the unobserved heterogeneity terms as a discrete function. The discrete factor approximation approach (Mroz, 1998) which borrows from the semi-parametric approach developed by Heckman and Singer (1984) for duration models with unobserved heterogeneity relaxes the joint normality assumption that is often assumed by researchers. Instead, the distribution of the unobserved heterogeneity is estimated along with the other parameters of interest in the model. The flexibility of the approach makes this approach advantageous to the researcher especially when the error terms may not be joint normally distributed.

Specifically, first assume that the error terms in the previous equations (equations 12, 13 and 14) can be decomposed as:

\[
\begin{align*}
\epsilon_{it} &= \rho_1 \cdot v + e_{1it} \\
\eta_{it}^c &= \rho_2^c \cdot v + e_{2it}^c & c &= 1, 2, 3, 4 \\
\eta_{it}^h &= \rho_3^h \cdot v + e_{3it}^h & h &= 1, 2, 3
\end{align*}
\]

(18)

where \(v, e_1, e_2\) and \(e_3\) are error terms that are independent of the exogenous variables in the model. \(\rho_1, \rho_2\) and \(\rho_3\) are often described as factor loading terms which can be interpreted as the effect of an unobserved factor \(v\) on the outcomes.\(^8\)

The empirical model can now be rewritten as

\[
O_{it+1}^* = \beta_0 + \beta_1 \cdot O_{it} + \sum_{c=2}^{4} \beta_2^c \cdot C_{it}^c + \sum_{h=2}^{3} \beta_3^h \cdot H_{it}^h + \beta_4 \cdot W_{it} + \rho_1 \cdot v + e_{1it}
\]

\[
O_{it+1} = \begin{cases} 
1 & \text{If Obese} \\
0 & \text{Otherwise}
\end{cases}
\]

(19)

\(^8\)In the case of a continuous outcome, it is in many cases possible to estimate the model using a fixed effects estimation approach. In this paper, where the outcome of interest (obesity) is a binary indicator, fixed effect approaches, where a differencing approach is commonly used, cannot be implemented and thus the model is estimated using a joint estimation approach. Furthermore, under the fixed effects approach coefficient estimates can only be determined for variables that vary over time because those that did not change will be eliminated under a differencing approach.
\[ V^c_{it} = \delta_0^c + \delta_1^c \cdot O_{it} + \delta_2^c \cdot W_{it} + \delta_3^c \cdot R_{it} + \rho_2^c \cdot v + e_{2it} \]  \quad c = 1, 2, 3, 4

\[ C^c_{it} = \begin{cases} 
1 & \text{If } V^c_{it} > V^{c'}_{it} \quad \forall c \neq c' \in [1, 2, 3, 4] \\
0 & \text{Otherwise}
\end{cases} \]

\[ V^h_{it} = \delta_0^h + \delta_1^h \cdot O_{it} + \delta_2^h \cdot W_{it} + \delta_3^h \cdot R_{it} + \rho_3^h \cdot v + e_{3it} \]  \quad h = 1, 2, 3

\[ H^h_{it} = \begin{cases} 
1 & \text{If } V^h_{it} > V^{h'}_{it} \quad \forall h \neq h' \in [1, 2, 3] \\
0 & \text{Otherwise}
\end{cases} \]

Assuming that \( e_2 \) and \( e_3 \) are type-I extreme value distributed, the child care and maternal employment choice probabilities conditional on the unobserved heterogeneity component \( v \) can be written as

\[ Pr(C^c_{it} = 1|v) = \frac{\exp(\delta_0^c + \delta_1^c \cdot O_{it} + \delta_2^c \cdot W_{it} + \delta_3^c \cdot R_{it} + \rho_2^c \cdot v)}{1 + \sum_{k=2}^{4} \exp(\delta_0^k + \delta_1^k \cdot O_{it} + \delta_2^k \cdot W_{it} + \delta_3^k \cdot R_{it} + \rho_2^k \cdot v)} \]  \quad \forall c \in [1, 2, 3, 4]

(22)

\[ Pr(H^h_{it} = 1|v) = \frac{\exp(\delta_0^h + \delta_1^h \cdot O_{it} + \delta_2^h \cdot W_{it} + \delta_3^h \cdot R_{it} + \rho_3^h \cdot v)}{1 + \sum_{k=2}^{3} \exp(\delta_0^k + \delta_1^k \cdot O_{it} + \delta_2^k \cdot W_{it} + \delta_3^k \cdot R_{it} + \rho_3^k \cdot v)} \]  \quad \forall h \in [1, 2, 3]

(23)

The health production function can be expressed as a binary logit where the outcome is the probability that the child is obese \( (O_{ijt+1} = 1) \)

\[ Pr(O_{it+1} = 1|v) = \frac{\exp(\beta_0 + \beta_1 \cdot O_{it} + \sum_{c=2}^{4} \beta_2^c \cdot C^c_{it} + \sum_{h=2}^{3} \beta_3^h \cdot H^h_{it} + \beta_4 \cdot W_{it} + \rho_1 \cdot v)}{1 + \exp(\beta_0 + \beta_1 \cdot O_{it} + \sum_{c=2}^{4} \beta_2^c \cdot C^c_{it} + \sum_{h=2}^{3} \beta_3^h \cdot H^h_{it} + \beta_4 \cdot W_{it} + \rho_1 \cdot v)} \]

(24)
Conditional on the heterogeneity factor $v$, the conditional probability for individual $i$ is

$$L_i(\Theta | v) = \prod_{t=1}^{T} \{Pr(O_{it+1} = 1|v)^{O_{it+1}} [1 - Pr(O_{it+1} = 1|v)]^{1-O_{it+1}}$$

$$\times Pr(O_{i1} = 1|v)^{O_{i1}} [1 - Pr(O_{i1} = 1|v)]^{1-O_{i1}}$$

$$\times \prod_{c=1}^{4} Pr(C_{ct} = 1|v)^{C_{ct}} \times \prod_{h=1}^{3} Pr(H_{ht} = 1|v)^{H_{ht}} \}$$

(25)

where $\Theta$ are the variables in the models that are to be estimated. The typical estimation approach would assume a distribution $f(v)$ to get the unconditional distribution by integrating over the unobserved heterogeneity:

$$L_i(\Theta) = \int_{-\infty}^{\infty} \prod_{t=1}^{T} L_i(\Theta | v) f(v) dv$$

(26)

Figure 1: Discrete Factor Approximation Approach

Instead, similarly to the approach used by Heckman and Singer (1984) the discrete factor approximation approach assumes a more flexible distribution of the unobserved component by approximating a discrete distribution of the conditional distribution function.
To describe this method more specifically, suppose that there exists a variable $v$ with a probability distribution function, $f(v)$ as shown in Figure 1. One way to estimate the cumulative distribution function $F(v)$ would be to integrate over an assumed distribution function (it is most often the case that the function is normally distributed). However, another way to integrate out over the distribution would be to discretize the function into $k$ points of support, and to estimate a weighted sum. In effect one estimates the probability weight $\pi_k$ which is the probability that $v$ takes on the value $a_k$ and sums over the possible mass points weighted by the probability of each mass point. This same methodology is used to estimate the model under a discrete factors approximation approach where the distribution is discretized and the mass point and probability weights are estimated together with the other parameters of the model.

Therefore, the unconditional probability can be written as a weighted sum over the mass points

$$L_t(\Theta, \omega) = \sum_{r=1}^{R} \omega_r \cdot L_i(\Theta | v_r)$$

(27)

where $R$ is the number of mass points and $\omega_r$ is the probability that the unobserved heterogeneity component takes on the value $v_r$.

Lastly, the likelihood function can be written as:

$$L(\Theta, \omega) = \prod_{i=1}^{N} L_i(\Theta, \omega)$$

(28)

Last but not least, one issue that has yet to be discussed in this paper is a problem often referred to as the initial conditions problem. Going back to equation (25) the probability of obesity at time $t + 1$ is a function of exogenous characteristics of the individual as well as obesity status in the previous period ($O_{ijt}$). The problem arises because of the term $Pr(O_{ij1} = 1 | v)^{O_{ij1}}$ which is the period 1 probability of observing that an individual is obese conditional on the unobserved heterogeneity component without any information on the previous state. Therefore, the initial probability of obesity cannot be regarded as being exogeneous in the model.

The intial conditions problem has been discussed in great depth and solutions have been devised to the problem. The first solution is to assume that the initial period is exogeneous so that probabiltiy
in the first period is independent of the unobserved heterogeneity term. This may work in cases where we observe the entire history of an individual. For instance, suppose that we are looking at the impact of a prenatal care program on breastfeeding duration. In estimating the effect, it is usually the case that individuals who breastfeed from the initial period will continue to breastfeed their child. If we can observe each woman from the time at which they gave birth, then we may be able to assume that the initial state is exogenous to the model.

However, exogeneity of the initial state is often inappropriate and it would be hard to argue in this paper that the child’s obesity status in the first period is exogenous. Therefore, I apply a method in which the initial state probability is modeled as a function of as much pre-sample information that I have available.

5 Data

5.1 Construction of Individual Characteristics, Child Care and Employment Variables

I use data from the Early Childhood Longitudinal Study Kindergarten Class of 1998-1999 (ECLS-K). The ECLS-K has followed a nationally representative sample of 21,260 kindergarteners since the fall of 1998. During the first year of the data collection, 1998-1999 (kindergarten year), surveys were conducted in the fall and the spring. Follow-up surveys were conducted in the fall and spring of 1999-2000 (when most children were in first grade), spring of 2002 (when most children were in the third grade), and spring of 2004 (when most children were in the fifth grade). Each survey contains information from interviews with the individual child, parent or caregiver, and school teachers and administrators.

The ECLS-K longitudinal kindergarten-fifth grade file (available from the National Center for Educational Studies) merges data from the four survey years. In my research, I do not use data from the fall of the kindergarten year, because many of the key variables I needed were not included in the survey, and the fall of the first grade year (1999), because only 20% of the original sample was interviewed. The data is well suited for this research because it collects detailed information on the child’s emotional, cognitive, and physiological well-being, and assessments of the child’s home and school environment in addition to the standard demographic information (e.g. age, sex,
grade, race, etc.). Furthermore, using restricted use geocode data, available through a contract with the U.S. Department of Education, I can identify the State of residence of each child and match him/her with State laws and policy variables that are used as instruments (specifics of the instruments used can be found in Section 5.2).

Using data from the parent/guardian interview, I construct overweight and obesity indicators for each child. The standard method for determining obesity status is to estimate the Body Mass Index (BMI), a ratio of an individual’s weight in kilograms to height in meters squared. A BMI of greater than 25 indicates overweight and greater than 30 indicates obesity. For children (ages 2-20) however, BMI-for-age-and-sex percentiles are used to determine obesity and overweight status. Using growth charts available from the CDC, a child is considered overweight if his/her BMI exceeds the 85th percentile for his/her age and sex group and obese if BMI is greater than the 95th percentile.

I constructed four child care variables using information about the number of hours spent in child care. The four variables are indicators of whether the child spent zero, between zero and ten, between ten and twenty, and more than twenty hours per week in child care. In addition to time spent in child care, the survey collects information on the location and type (e.g. informal child care, defined as care by a relative or a family member, or formal child care defined as care given in a formal child care center) of child care received which I hope to use in my future analysis to examine whether there are differences in the impact of time spent in child care by location or type.

I also construct a detailed employment history of the mother. I created three variables which are indicators of whether the mother worked zero, between zero and twenty, and between twenty and forty hours per week. Unfortunately, data on wages is unavailable and family income was only collected in the fall of the kindergarten year. I therefore do not include maternal income nor total family income in the estimations.

Background information about the child on numerous dimensions is collected in the survey and is included in the estimation of the obesity equation. In particular I use: the child’s age (in months), race and sex. The child’s age in months was estimated by taking the month and year of the survey and subtracting the birth month and year of the child. Two indicator variables, black and hispanic, are equal to one if the child is black or hispanic. The child’s sex indicator is set to one if the child is male and zero otherwise. Four indicator variables for the mother’s education level
are constructed: less than high school, high school graduate or equivalent to a high school degree, some college, and college education or more. A list and description of the variables are available in Table 1.

Of the 21,260 children who were surveyed in the base year, the above information may be missing during certain survey periods. That being said, there should be a maximum of four observations (fall 1998, spring 2000, spring 2002, and spring 2004) for each individual surveyed. The total person-year observations that I have over the four surveys is 70,260. I restrict the sample to observations where the variables listed in Table 1 are not missing. After I do so, I observe a total of 48,566 observations spanning the four survey periods. In Table 3 I present the number of observations remaining after dropping observations in which key variables were missing. It should be noted that there was very little difference in the means when comparing the original to the selected sample.

5.2 Construction of Instruments

As described in the empirical section, I am concerned with the possible endogeneity of the child care and maternal employment variables. Specifically, there may be unobserved (by the researcher) traits that may be influencing both maternal employment and child care, and the outcome of interest (obesity). Thus, my solution is to control for this possible endogeneity problem by finding variables that are correlated with the child care or maternal employment variables, but are not directly correlated with the probability that the child is obese. I will construct several instruments using State laws and policies which I will collect from the following sources:

1. State Welfare and Child Care Rules:
   Office of Family Assistance (US Dept. of Health and Human Services), National Center for Children in Poverty (Columbia University), Administration for Children and Families (US Dept. of Health and Human Services)

2. Labor Market Conditions (e.g. unemployment rates):

3. Food prices:
   Census of the Retail Trade (Bureau of the Census)
5.3 Descriptive Statistics

I present summary statistics in Table 4. About 35% and 22% of the sample are overweight and obese, respectively, which is comparable to estimates reported by the CDC which used data from the National Health and Examination Surveys. I find that a very large proportion of children (over 50%) spend no time in child care during the week and around 20% of children spend less than ten hours in child care per week. Most mothers are either unemployed or are full time workers (work more than twenty hours per week). The average age of the child is 95 months or around eight years of age which is around the time that the child is in the third grade. A majority of the mothers (around 75%) have less than a college education and around 75% are married.

6 Results

6.1 The Probit Regression

I begin by estimating a probit model of obesity. I regress obesity on indicators for child care, maternal employment, obesity in the previous period, and exogenous characteristics of the mother and child that are listed in Table 1.

In Tables 5 and 6, I present marginal effects of child care and maternal employment on the probability of being obese. Marginal effects are estimated for the full sample, stratified by sex, race, and mother’s education level. The standard errors were obtained by bootstrapping with 100 draws. I find that in most cases, the effect of child care is positive on the effect of obesity. For instance, in the full sample, child care between zero and ten hours per week is associated with roughly an 1% significant increase in the probability that the child is obese. When the sample is stratified by sex, the effect of child care continues to be positive and significant for females, but the sign is negative for males. Compared to the full sample, the magnitude of the effect of child care also increases for females. For example, there is roughly a 2% increase in the obesity probability for child care between zero and ten hours compared to no child care.

The effect of maternal employment tends to be negative if the mother works part time, but positive if she works full time (greater than 20 hours per week). I find that compared to not working, employment of more than 20 hours per week is associated with an 1.1% increase in the
obesity probability for the full sample. However, it should be noted that these results may be misleading since I do not control for possible self-selection for these inputs in which case the results are biased.

In Tables 7 and 8, I provide coefficient estimates for the other parameters in the models estimated in Table 5. The effect of age and race on obesity are both positive and significant. Furthermore, obesity in the previous period is a positive and a highly significant predictor of current period obesity. A mother’s level of education has a negative and significant impact on the probability of being obese. It should be noted that these initial estimation results are comparable to previous research that also examined the effect of these key variables on obesity risk.

7 Future Research Goals

This paper seeks to estimate the impact of child care and maternal employment on a child’s probability of obesity using three different estimation approaches: probit regression, bivariate probit estimation, and the discrete factor approximation method. Preliminary results where I do not control for potential endogeneity bias indicate that the effect of child care and maternal full-time employment on obesity are positive and (in some cases) significant.

I am currently in the process of waiting for the restricted use data from the National Center for Educational Studies. With these State identifiers, I will be able to match State variables to individuals in my dataset and estimate the model using a bivariate probit and discrete factor approximation approach. I also hope to conduct simulations where I estimate the impact of changes in State laws and policies on child care and employment, and subsequently on obesity.

In estimating the probit model I find that the effects of child care and employment differ in magnitude and in some cases sign for different subgroups and I hope to research this further. Additionally, I hope to include the location and type of child care into the model. For instance, the effect of time spent in child care on obesity may differ depending on whether the child was being cared for by a relative or in a child care center.
Table 1: Variable Description

<table>
<thead>
<tr>
<th>Variable</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Obese</td>
<td>Indicator equal to 1 if child’s BMI is greater than the 95th percentile for age and sex</td>
</tr>
<tr>
<td>Overweight</td>
<td>Indicator equal to 1 if child’s BMI is greater than the 85th percentile for age and sex</td>
</tr>
<tr>
<td>Child Care</td>
<td></td>
</tr>
<tr>
<td>0hrs</td>
<td>Indicator equal to one if hours in child care is 0</td>
</tr>
<tr>
<td>0-10hrs</td>
<td>Indicator equal to one if hours in child care is between 0-10 hrs/wk</td>
</tr>
<tr>
<td>10-20hrs</td>
<td>Indicator equal to one if hours in child care is between 10-20 hrs/w</td>
</tr>
<tr>
<td>≥ 20hrs</td>
<td>Indicator equal to one if hours in child care is ≥ 20 hrs/w</td>
</tr>
<tr>
<td>Mom’s Employment</td>
<td></td>
</tr>
<tr>
<td>0hrs</td>
<td>Indicator equal to one if number of hrs/wk worked equals 0</td>
</tr>
<tr>
<td>0-20hrs</td>
<td>Indicator equal to one if hours in number of hrs/wk worked is between 0-20</td>
</tr>
<tr>
<td>≥ 20hrs</td>
<td>Indicator equal to one if number of hrs/wk worked is ≥ 20</td>
</tr>
<tr>
<td>Male</td>
<td>Indicator equal to 1 if male</td>
</tr>
<tr>
<td>Age</td>
<td>Child’s age in months: Date of interview-Data Born</td>
</tr>
<tr>
<td>Black</td>
<td>Indicator equal to 1 if black</td>
</tr>
<tr>
<td>Hispanic</td>
<td>Indicator equal to 1 if Hispanic</td>
</tr>
<tr>
<td>Mom’s age</td>
<td>Age of mother at interview date in years</td>
</tr>
<tr>
<td>Mom’s Education</td>
<td></td>
</tr>
<tr>
<td>&lt; High School</td>
<td>Indicator equal to 1 if mom has &lt; a HS education</td>
</tr>
<tr>
<td>High School</td>
<td>Indicator equal to 1 if mom has a HS education (nothing byeond)</td>
</tr>
<tr>
<td>Some College</td>
<td>Indicator equal to 1 if mom attended college but did not graduate</td>
</tr>
<tr>
<td>≥ College</td>
<td>Indicator equal to 1 if High mom has atleast college diploma</td>
</tr>
<tr>
<td>Household size</td>
<td>Number of people in the household</td>
</tr>
<tr>
<td>Married</td>
<td>Indicator equal to 1 if mom is married</td>
</tr>
</tbody>
</table>
Table 2: List of Exclusion Restrictions

<table>
<thead>
<tr>
<th>Variable Description</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>exclusion restrictions</td>
<td>Descriptions of the variables here</td>
</tr>
</tbody>
</table>

Table 3: Determination of Sample

<table>
<thead>
<tr>
<th>Variable</th>
<th>Sample Size*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Original Sample</td>
<td>70,260</td>
</tr>
<tr>
<td>Dependent Variable</td>
<td></td>
</tr>
<tr>
<td>Obese</td>
<td>56,108</td>
</tr>
<tr>
<td>Explanatory Variables</td>
<td></td>
</tr>
<tr>
<td>Child care</td>
<td>50,597</td>
</tr>
<tr>
<td>Maternal employment</td>
<td>50,597</td>
</tr>
<tr>
<td>Child’s sex</td>
<td>49,238</td>
</tr>
<tr>
<td>Child’s age</td>
<td>49,236</td>
</tr>
<tr>
<td>Child’s race</td>
<td>49,194</td>
</tr>
<tr>
<td>Mother’s marital Status</td>
<td>48,666</td>
</tr>
<tr>
<td>Mother’s age</td>
<td>48,566</td>
</tr>
<tr>
<td>Final Sample</td>
<td>48,566</td>
</tr>
</tbody>
</table>

* The sample sizes shown represent the number of observations after excluding the observations for which the given variable were missing.
Table 4: Summary Statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Mean</th>
<th>(Standard Error)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percent Obese</td>
<td>21.79</td>
<td>(41.28)</td>
</tr>
<tr>
<td>Percent Overweight</td>
<td>35.71</td>
<td>(47.92)</td>
</tr>
<tr>
<td>Child Care</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 hrs (%)</td>
<td>58.84</td>
<td>(49.21)</td>
</tr>
<tr>
<td>0-10 hrs (%)</td>
<td>21.92</td>
<td>(41.37)</td>
</tr>
<tr>
<td>10-20 hrs (%)</td>
<td>12.11</td>
<td>(32.63)</td>
</tr>
<tr>
<td>&gt;20 hrs (%)</td>
<td>7.12</td>
<td>(32.63)</td>
</tr>
<tr>
<td>Mom’s Employment</td>
<td></td>
<td></td>
</tr>
<tr>
<td>0 hrs (%)</td>
<td>28.78</td>
<td>(45.27)</td>
</tr>
<tr>
<td>0-20 hrs (%)</td>
<td>7.42</td>
<td>(26.21)</td>
</tr>
<tr>
<td>&gt;20 hrs (%)</td>
<td>63.80</td>
<td>(48.06)</td>
</tr>
<tr>
<td>Percent Male</td>
<td>50.70</td>
<td>(50.00)</td>
</tr>
<tr>
<td>Age (months)</td>
<td>95.73</td>
<td>(24.34)</td>
</tr>
<tr>
<td>Percent black</td>
<td>12.04</td>
<td>(32.54)</td>
</tr>
<tr>
<td>Percent Hispanic</td>
<td>17.00</td>
<td>(37.56)</td>
</tr>
<tr>
<td>Mom’s age</td>
<td>36.21</td>
<td>(6.96)</td>
</tr>
<tr>
<td>Mom’s Education</td>
<td></td>
<td></td>
</tr>
<tr>
<td>&lt; High School (%)</td>
<td>12.52</td>
<td>(33.10)</td>
</tr>
<tr>
<td>High School (%)</td>
<td>29.34</td>
<td>(45.53)</td>
</tr>
<tr>
<td>Some college (%)</td>
<td>32.43</td>
<td>(46.81)</td>
</tr>
<tr>
<td>≥ college (%)</td>
<td>25.71</td>
<td>(43.70)</td>
</tr>
<tr>
<td>Percent Married</td>
<td>75.00</td>
<td>(43.30)</td>
</tr>
<tr>
<td>Sample Size</td>
<td>48,566</td>
<td></td>
</tr>
</tbody>
</table>
Table 5: Marginal Effects of Child Care and Maternal Employment on the Probability of Being Obese

<table>
<thead>
<tr>
<th>Variable</th>
<th>Full Sample</th>
<th>Female</th>
<th>Male</th>
<th>White</th>
<th>Black</th>
<th>Hispanic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Child Care</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-10 hrs</td>
<td>0.990**</td>
<td>2.211***</td>
<td>-0.071</td>
<td>0.870*</td>
<td>2.512*</td>
<td>0.566</td>
</tr>
<tr>
<td></td>
<td>(0.424)</td>
<td>(0.779)</td>
<td>(0.538)</td>
<td>(0.494)</td>
<td>(1.492)</td>
<td>(1.278)</td>
</tr>
<tr>
<td>10-20 hrs</td>
<td>0.387</td>
<td>2.195**</td>
<td>-1.127*</td>
<td>0.076</td>
<td>2.378</td>
<td>0.283</td>
</tr>
<tr>
<td></td>
<td>(0.523)</td>
<td>(1.019)</td>
<td>(0.623)</td>
<td>(0.777)</td>
<td>(1.699)</td>
<td>(1.368)</td>
</tr>
<tr>
<td>&gt;20 hrs</td>
<td>0.148</td>
<td>0.142</td>
<td>0.200</td>
<td>0.075</td>
<td>1.854</td>
<td>-0.504</td>
</tr>
<tr>
<td></td>
<td>(0.737)</td>
<td>(1.067)</td>
<td>(0.920)</td>
<td>(0.910)</td>
<td>(1.749)</td>
<td>(1.570)</td>
</tr>
<tr>
<td>Maternal</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Employment</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-20 hrs</td>
<td>-1.143*</td>
<td>0.068</td>
<td>-2.385***</td>
<td>-0.703</td>
<td>-0.357</td>
<td>-3.020*</td>
</tr>
<tr>
<td></td>
<td>(0.683)</td>
<td>(1.290)</td>
<td>(0.750)</td>
<td>(0.799)</td>
<td>(3.366)</td>
<td>(1.811)</td>
</tr>
<tr>
<td>&gt;20 hrs</td>
<td>1.103**</td>
<td>0.748</td>
<td>1.390***</td>
<td>1.312***</td>
<td>0.732</td>
<td>0.847</td>
</tr>
<tr>
<td></td>
<td>(0.465)</td>
<td>(0.750)</td>
<td>(0.536)</td>
<td>(0.470)</td>
<td>(1.406)</td>
<td>(1.044)</td>
</tr>
<tr>
<td>Sample Size</td>
<td>32,422</td>
<td>16,023</td>
<td>16,399</td>
<td>23,223</td>
<td>3,768</td>
<td>5,431</td>
</tr>
</tbody>
</table>

Note: Standard errors are in parentheses and bootstrapped with 100 draws. All marginal effects and standard errors are multiplied by 100.

*** indicates significance at the 1% level, ** 5% level, * 10% level
Table 6: Marginal Effects of Child Care and Maternal Employment on the Probability of Being Obese

<table>
<thead>
<tr>
<th>Variable</th>
<th>Less than HS</th>
<th>High School</th>
<th>Some College</th>
<th>College or more</th>
</tr>
</thead>
<tbody>
<tr>
<td>Child Care</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-10 hrs</td>
<td>0.873</td>
<td>2.514***</td>
<td>-0.033</td>
<td>0.773</td>
</tr>
<tr>
<td></td>
<td>(1.839)</td>
<td>(0.891)</td>
<td>(0.732)</td>
<td>(0.735)</td>
</tr>
<tr>
<td>10-20 hrs</td>
<td>-2.008</td>
<td>0.764</td>
<td>0.159</td>
<td>0.982</td>
</tr>
<tr>
<td></td>
<td>(1.630)</td>
<td>(1.082)</td>
<td>(0.925)</td>
<td>(1.103)</td>
</tr>
<tr>
<td>&gt;20 hrs</td>
<td>-1.516</td>
<td>-0.046</td>
<td>1.333</td>
<td>-0.386</td>
</tr>
<tr>
<td></td>
<td>(2.411)</td>
<td>(1.282)</td>
<td>(1.276)</td>
<td>(1.580)</td>
</tr>
<tr>
<td>Maternal Employment</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>0-20 hrs</td>
<td>-3.173***</td>
<td>-3.372**</td>
<td>-1.230</td>
<td>1.353</td>
</tr>
<tr>
<td></td>
<td>-(0.386)</td>
<td>(1.387)</td>
<td>(1.141)</td>
<td>(1.243)</td>
</tr>
<tr>
<td>&gt;20 hrs</td>
<td>1.074***</td>
<td>0.301</td>
<td>1.534**</td>
<td>1.646*</td>
</tr>
<tr>
<td></td>
<td>-(0.138)</td>
<td>(0.920)</td>
<td>(0.759)</td>
<td>(0.903)</td>
</tr>
</tbody>
</table>

Sample Size 3,925 9,515 10,529 8,453

Note: Standard errors are in parentheses and bootstrapped with 100 draws. All marginal effects and standard errors are multiplied by 100.

*** indicates significance at the 1% level, ** 5% level, * 10% level
Table 7: Coefficient Estimates from Probit Analysis

<table>
<thead>
<tr>
<th>Variable</th>
<th>Full Sample</th>
<th>Female</th>
<th>Male</th>
<th>White</th>
<th>Black</th>
<th>Hispanic</th>
</tr>
</thead>
<tbody>
<tr>
<td>Obesity</td>
<td>2.574 ***</td>
<td>2.548 ***</td>
<td>2.575 ***</td>
<td>2.625 ***</td>
<td>2.424 ***</td>
<td>2.489 ***</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.044)</td>
<td>(0.039)</td>
<td>(0.037)</td>
<td>(0.079)</td>
<td>(0.063)</td>
</tr>
<tr>
<td>Male</td>
<td>-0.564 ***</td>
<td>-</td>
<td>-</td>
<td>-0.566 ***</td>
<td>-0.731 ***</td>
<td>-0.443 ***</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td></td>
<td></td>
<td>(0.023)</td>
<td>(0.056)</td>
<td>(0.045)</td>
</tr>
<tr>
<td>Age</td>
<td>0.109 ***</td>
<td>0.125 ***</td>
<td>0.085 ***</td>
<td>0.112 ***</td>
<td>0.098 ***</td>
<td>0.109 ***</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.010)</td>
<td>(0.011)</td>
<td>(0.009)</td>
<td>(0.021)</td>
<td>(0.017)</td>
</tr>
<tr>
<td>Age squared</td>
<td>-0.001 ***</td>
<td>-0.001 ***</td>
<td>0.000 ***</td>
<td>-0.001 ***</td>
<td>0.000 ***</td>
<td>-0.001 ***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Black</td>
<td>0.120 ***</td>
<td>0.233 ***</td>
<td>-0.016</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.031)</td>
<td>(0.042)</td>
<td>(0.050)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.089 ***</td>
<td>0.056</td>
<td>0.132 ***</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>(0.026)</td>
<td>(0.036)</td>
<td>(0.039)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mother’s age</td>
<td>0.002</td>
<td>-0.002</td>
<td>0.006 **</td>
<td>0.000</td>
<td>0.004</td>
<td>0.004</td>
</tr>
<tr>
<td></td>
<td>(0.001)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.002)</td>
<td>(0.003)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Mother Education</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>HS grad</td>
<td>-0.117 ***</td>
<td>-0.095 **</td>
<td>-0.129 ***</td>
<td>-0.121 **</td>
<td>-0.067</td>
<td>-0.138 **</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.044)</td>
<td>(0.047)</td>
<td>(0.048)</td>
<td>(0.075)</td>
<td>(0.055)</td>
</tr>
<tr>
<td>Some college</td>
<td>-0.160 ***</td>
<td>-0.118 ***</td>
<td>-0.197 ***</td>
<td>-0.169 ***</td>
<td>-0.054</td>
<td>-0.215 ***</td>
</tr>
<tr>
<td></td>
<td>(0.032)</td>
<td>(0.045)</td>
<td>(0.048)</td>
<td>(0.048)</td>
<td>(0.079)</td>
<td>(0.059)</td>
</tr>
<tr>
<td>College+</td>
<td>-0.326 ***</td>
<td>-0.298 ***</td>
<td>-0.351 ***</td>
<td>-0.339 ***</td>
<td>-0.157</td>
<td>-0.304 ***</td>
</tr>
<tr>
<td></td>
<td>(0.036)</td>
<td>(0.049)</td>
<td>(0.054)</td>
<td>(0.050)</td>
<td>(0.111)</td>
<td>(0.082)</td>
</tr>
<tr>
<td>Household size</td>
<td>-0.011</td>
<td>-0.008</td>
<td>-0.015</td>
<td>0.004</td>
<td>-0.030</td>
<td>-0.037 **</td>
</tr>
<tr>
<td></td>
<td>(0.007)</td>
<td>(0.010)</td>
<td>(0.011)</td>
<td>(0.009)</td>
<td>(0.017)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Married</td>
<td>-0.054</td>
<td>-0.031</td>
<td>-0.081 **</td>
<td>-0.095 ***</td>
<td>-0.044</td>
<td>0.030</td>
</tr>
<tr>
<td></td>
<td>(0.024)</td>
<td>(0.033)</td>
<td>(0.037)</td>
<td>(0.031)</td>
<td>(0.060)</td>
<td>(0.051)</td>
</tr>
<tr>
<td>Sample Size</td>
<td>32,422</td>
<td>16,023</td>
<td>16,399</td>
<td>23,223</td>
<td>3,768</td>
<td>5,431</td>
</tr>
<tr>
<td>Pseudo $R^2$</td>
<td>0.425</td>
<td>0.389</td>
<td>0.455</td>
<td>0.424</td>
<td>0.413</td>
<td>0.428</td>
</tr>
</tbody>
</table>

Note: Standard Errors (in parentheses) are adjusted for individual level clustering.  
*** indicates significance at the 1% level, ** 5% level, * 10% level.
Table 8: Coefficient Estimates from Probit Analysis

<table>
<thead>
<tr>
<th>Variable</th>
<th>Less than HS</th>
<th>School</th>
<th>Some College</th>
<th>College or more</th>
</tr>
</thead>
<tbody>
<tr>
<td>Obesity</td>
<td>2.427 ***</td>
<td>2.641 ***</td>
<td>2.625 ***</td>
<td>2.515 ***</td>
</tr>
<tr>
<td></td>
<td>(0.077)</td>
<td>(0.055)</td>
<td>(0.052)</td>
<td>(0.061)</td>
</tr>
<tr>
<td>Male</td>
<td>-0.475 ***</td>
<td>-0.563 ***</td>
<td>-0.609 ***</td>
<td>-0.556 ***</td>
</tr>
<tr>
<td></td>
<td>(0.051)</td>
<td>(0.035)</td>
<td>(0.034)</td>
<td>(0.040)</td>
</tr>
<tr>
<td>Age</td>
<td>0.109 ***</td>
<td>0.114 ***</td>
<td>0.127 ***</td>
<td>0.081 ***</td>
</tr>
<tr>
<td></td>
<td>(0.019)</td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.015)</td>
</tr>
<tr>
<td>Age squared</td>
<td>-0.001</td>
<td>-0.001 ***</td>
<td>-0.001 ***</td>
<td>0.000 ***</td>
</tr>
<tr>
<td></td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>Black</td>
<td>0.042</td>
<td>0.114 **</td>
<td>0.124 **</td>
<td>0.227 ***</td>
</tr>
<tr>
<td></td>
<td>(0.075)</td>
<td>(0.052)</td>
<td>(0.054)</td>
<td>(0.088)</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.085</td>
<td>0.077 *</td>
<td>0.047</td>
<td>0.170 **</td>
</tr>
<tr>
<td></td>
<td>(0.055)</td>
<td>(0.047)</td>
<td>(0.049)</td>
<td>(0.073)</td>
</tr>
<tr>
<td>Mother’s age</td>
<td>0.002</td>
<td>0.005 *</td>
<td>-0.001</td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.003)</td>
<td>(0.004)</td>
</tr>
<tr>
<td>Household size</td>
<td>-0.015</td>
<td>-0.013</td>
<td>-0.020</td>
<td>0.019</td>
</tr>
<tr>
<td></td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.013)</td>
<td>(0.019)</td>
</tr>
<tr>
<td>Married</td>
<td>-0.025</td>
<td>-0.011</td>
<td>-0.100</td>
<td>-0.121</td>
</tr>
<tr>
<td></td>
<td>(0.057)</td>
<td>(0.041)</td>
<td>(0.043)</td>
<td>(0.067)</td>
</tr>
<tr>
<td>Sample Size</td>
<td>3,925</td>
<td>9,515</td>
<td>10,529</td>
<td>8,453</td>
</tr>
<tr>
<td>Pseudo $R^2$</td>
<td>0.394</td>
<td>0.437</td>
<td>0.436</td>
<td>0.399</td>
</tr>
</tbody>
</table>

Note: Standard Errors (in parentheses) are adjusted for individual level clustering.
*** indicates significance at the 1% level, ** 5% level, * 10% level
References


Appendix A

Appendix B: Formulation of the Bellman Equation

In this section, I outline a generic multi-period utility maximization problem and derive the Bellman equation. I begin with a generic $T$ period utility maximization problem to show how the Bellman equation is constructed. This methodology can be easily applied to the utility maximization problem presented in Section 3.

Suppose the following utility maximization problem:

$$
\max U(C_1, C_2, ..., C_n) = \sum_{t=0}^{T} \beta^t E_t U(C_t) \quad \text{s.t.} \quad I_{t+1} = (I_t - C_t) \cdot (1 + r_t)
$$

(B1)

where $C_t$ is a consumption at time $t$ (and the choice variable), $I_t$ is income at time $t$, $r_t$ is the interest rate, and $\beta$ is a discount factor. This problem also assumes that the utility function is additively separable.

First, to simplify this problem, assume that there are only 2 periods: $T-1$ and $T$. The utility maximization problem can then be written as

$$
\max U(C_{T-1}) + \beta E_{T-1} U(C_T) \quad \text{s.t.} \quad I_T = (I_{T-1} - C_{T-1}) \cdot (1 + r_{T-1})
$$

(B2)

at time $T$, the individual will choose to consume his whole income so that the Bellman equation for this two period problem can be written as

$$
V_{T-1}(I_{T-1}) = \max U(C_{T-1}) + \beta E_T U[(I_{T-1} - C_{T-1}) \cdot (1 + r_{T-1})]
$$

(B3)

Now, suppose that there are 3 periods, T-2, T-1, and T and the utility maximization problem is the following:

$$
\max U(C_{T-2}) + \beta E_{T-2} U(C_{T-1}) + \beta^2 E_T U[(I_{T-1} - C_{T-1}) \cdot (1 + r_{T-1})] \quad \text{s.t.} \quad I_{T-1} = (I_{T-2} - C_{T-2}) \cdot (1 + r_{T-2})
$$
Since the utility function is additively separable and we know that the maximization of the last two periods is equal to $V_{T-1}(I_{T-1})$, the Bellman equation for a three period utility maximization problem can be rewritten as

$$V_{T-2}(I_{T-2}) = \max U(C_{T-2}) + \beta E_{T-1}V[(I_{T-2} - C_{T-2}) \cdot (1 + r_{T-2})]$$

(B5)

As this shows, a $t$ period utility maximization problem can be written as a two period optimization problem

$$V_t(I_t) = \max U(C_t) + \beta E_{t+1}V[(I_t - C_t) \cdot (1 + r_t)]$$

(B6)