Childhood Obesity Risk and the Role of Primary Caregivers: A Triangular Semi-parametric Simultaneous Equations Approach

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Abstract

This essay investigates the impacts of primary care giver's (PCG) time allocation and food expenditure choices on childhood obesity using national panel study of income dynamic (PSID) data. A triangular system of equations is derived and estimated under parametric and semi-parametric model settings. The performances of the two modeling strategies are compared using predictive ability measures with the aid of bootstrap method. Test results suggest relatively better performance of the semi-parametric model than parametric model. Nevertheless, the comparison of the estimates from both parametric and semi-parametric estimation indicates no dramatic changes in our findings. Our results do not suggest significant impacts of PCG's labor force participation choices, involvement in children's outdoor activity, and household food expenditures on children's Body Mass Index (BMI). However, the estimates from both iterated seemingly unrelated regression (SUR) and semi-parametric polynomial estimation indicate that parents' BMI significantly influence children's BMI. Obese parents tend to have obese children. Furthermore, physical activity appears to have weak correlation with children's BMI. More physical activity time does not necessarily lead to lower BMI of children.

Keywords: Time Allocation, Childhood Obesity, Triangular System of Equations, Seemingly Unrelated Regression, Two-Stage Polynomial Regression

1. Introduction

The rate of childhood obesity has been growing rapidly over the past three decades. The prevalence of obesity among children aged 6 to 11 years and adolescents aged 12 to 19 years increased from 6.5% to 19.6% and from 5.0% to 18.1% respectively from 1980 to 2008 (National Center for Health Statistics 2004; Ogden et al. 2010). Childhood obesity is a complex phenomenon affected by a broad spectrum of biological, sociological, and economic factors. Some studies have suggested that certain factors are direct causes of childhood obesity while some studies indicate otherwise. For example, increased consumption of soft drinks (Ludwig et al. 2001; Troiano et al. 2004), snacking (Nielsen and Popkin; Cutler et al. 2003), and fast food (Paeratuku et al. 2003; Chou et al. 2004; Thompson et al. 2004) have been argued as causes of childhood obesity. However, the study of Rajeshwari et al. (2005) suggests that there is no significant positive relationship between sweetened beverage and children's Body Mass Index (BMI); Bandini et al. (2005) suggest that snacking does not appear to have impact on childhood overweigh; Ebbeling et al. (2004) indicate that children consuming more fast food are not more likely to be overweight and obese. Lack of physical activities is another issue that most studies have been arguing responsible for childhood obesity. Television watching is a good example of being blamed for causing less physical activities. However, Nielsen data indicate that viewing time of both younger children and teens had been falling between 1982 to1999 (Nielsen Media Research 2000). Indeed, the evidence is still mixed as beneficial effects of physical activities on health outcomes are unclear given that optimal intensities, volumes, and modalities are still inconclusive (Goran et al. 1999). What has caused the rapid increase of childhood obesity remains an open question, and given the mixed empirical evidence of the driven forces behind

the epidemic in literature, further investigation in a well-defined theoretical framework is warranted.

Childhood obesity at its roots is a function of energy intake and energy expended. The more the former exceeds the latter, the more weight a child will gain. Parents play a central role in children's energy intake and energy expenditure process since they influence children's diet composition, eating habits, physical activity patterns, and psychological and emotional status which affect metabolic rates. The primary care giver (PCG) who takes care of the children most of the time in a family and supervises children's activities is especially influential as she/he largely decides what the children eat, how much the children eat, the levels and intensity of physical activities, and the time of sedative activities. From the production point of view, the PCG purchases foods on the market and combines them with time in a health production function to produce "commodities"- the health outcomes of the children. Children's health outcomes enter the PCG's utility function as arguments. Time is a source of PCG's market income as well as an input of the health commodity. As a new area of the interest, PCG's influences on childhood obesity have been gaining increasing attention. Some studies have been conducted to examine these influences in a household production framework which helps shade light on the impacts of intra-household factors on childhood obesity (e.g., You and Davis 2010). However, there has been a lack of empirical studies using nationally representative data to investigate the role of PCG influencing childhood obesity risk. This paper intends to fill this gap by assessing the impacts of PCG's time allocation and food spending choices on children's Body Mass Index (BMI) using national panel study of income dynamics (PSID) data. Furthermore, we are aware that the validity of parametric model estimates relies heavily on the restrictive distributional assumptions and functional forms. For the first time in literature, this paper

introduces a semi-parametric approach to estimate a triangular simultaneous system of equations to investigate the influential factors on childhood obesity. The performances of the two modeling strategies are compared using predictive ability measures with the aid of bootstrap method.

The remainder of the paper proceeds as follows. First, we explain our theoretical framework. Next, empirical model and related econometric issues are discussed. Then we introduce the survey data used in the analysis, followed by a section discussing parametric and semi-parametric estimation results. After the result discussion, we compare the performance of the two different econometric models. The paper concludes with discussion focusing on the influential factors on childhood obesity and the application of proper econometric models.

2. Theoretical Framework

We define a child's health production function in terms of BMI as:

(1) $\text{BMI} = H(X^c, T_E^c, T_E^j; T_F, k^p, k^h, k^c, E)$

Where X^c is the amount of food consumed by the child, T_E^c is the physical activity time of the child, and T_E^j is the joint physical activity time of the PCG and the child. The separation of the physical activity time of the child captures the difference of the child's energy intake and consumption patterns with and without the presence of the PCG. The difference could be brought by the activity goals, beliefs, and habits of the PCG which influence the types and intensity of the child's activity. T_F is the PCG's food preparation time which could affect the food quality offered to the child. *h* represents the household head who is usually the husband in a traditional household, *p* represents the PCG. In this study, a PCG is defined as the wife who provides primary care to the children in a household. *c* represents the child. k^h, k^p, k^c describe the types of the head, the PCG and the child respectively. The type variables describe a set of biological,

genetic, and socio-demographic characteristics of the parents and child which affect the energy-to-weight conversion process of the child. E denotes the influential environmental factors on the child's BMI production.

Then the child's utility function is defined as:

(2) $v^c = v^c(X^c, X_0^c, BMI, T_E^c, T_E^j; k^c)$

Where X_0^c is the child's consumption of other goods.

The PCG's utility function which can be expressed as:

(3) $v^p = v^p(X^p, X_o^p, BMI, T_w^p, T_F, T_L, T_E^j, T_O; k^p, v^c)$

Where X^p is the amount of food consumed by the PCG, X_0^p is the PCG's consumption of other goods, T_W^p is the working time of PCG, T_L is the leisure time for the PCG, and T_O is the residual time of the PCG for other activities. The PCG's utility is conditional on the child's utility, implying that the PCG cares about the child's utility.

The budget constraints the PCG faces:

(4) $X^p + X^c + X^h + X_0^p + X_0^c + X_0^h = \sum w^i T_W^i + I$, $i = h, p$

Where X^h is the amount of food consumed by the head, X_0^h is the amount of other market goods consumed by the head, T_W^i are the working hours of the head and PCG, w^i are the wage rates of the head and PCG, and I is the other non-labor income of the household.

The time constraint that the PCG faces is:

(5) $T_W^p + T_F + T_L + T_E^j + T_O = T$

Hence, from the PCG's perspective, the maximization problem is:

$$\underset{\begin{pmatrix} X^p, X_o^p, T_W, T_F \\ T_E^j, T_L^w \end{pmatrix}}{Max} \quad v = v^p(X^p, X_o^p, BMI, T_w^p, T_F, T_L, T_E^j, T_O; k^p, v^c)$$

$$s.t. \begin{cases} X^p + X^c + X^h + X_0^p + X_0^c + X_0^h = \sum w^i T_W^i + I, i = h, p \\ T_W^p + T_F + T_L + T_E^j + T_O = T \end{cases}$$

Maximizing PCG's utility function subject to income and time constraints, we can derive a system of equations:

$$(6) \quad \begin{cases} T_W^P = T_W^P(w^p, w^h, T_W^h, I, k^h, k^p, k^c, E) \\ T_E^j = T_E^j(w^p, w^h, T_W^h, I, k^h, k^p, k^c, E) \\ X^c = X^c(w^p, w^h, T_W^h, I, k^h, k^p, k^c, E) \\ BMI = H(X^c, T_W^P, T_E^j, k^h, k^p, k^c, E) \end{cases}$$

The system consists of three reduced form equations and one structural equation to define the PCG's optimal time allocation and food expenditure choices. There are four variables, w^p, w^h, T_W^h, I, are in reduced form equations but not in the structural equation. Therefore the number of the excluded exogenous variables from the structural equation is larger than the number of the included right-hand-side endogenous variables in the structural equation. The order condition is thus satisfied, which is necessary for the structural equation to be identified.

3. Empirical Model

3.1 Model specification

Based on our theoretical model, a system of equations is specified assuming linear functional forms:

$$(1)\ PCGWKHR = f_1(PCGWage, HDWKHR, HDWage, NlabIncome, HDBMI, HDHealth, PCGBMI, PCGHealth, EmpMom, PCGage, PCGedu\ PCGwhite, Lunchpro, ActiveTime, ChildWhite, Childgender, Childage, Loved, NumChildren)$$

$$(2)\ PCGChildOutdoor = f_2(PCGWage, HDWKHR, HDWage, NlabIncome, HDBMI, HDHealth, PCGBMI, PCGHealth, EmpMom, PCGage, PCGedu\ PCGwhite, Lunchpro, ActiveTime, ChildWhite, Childgender, Childage, Loved, NumChildren)$$

$$(3)\ FoodExp = f_3(PCGWage, HDWKHR, HDWage, NlabIncome, HDBMI, HDHealth, PCGBMI, PCGHealth, EmpMom, PCGage, PCGedu\ PCGwhite, Lunchpro, ActiveTime, ChildWhite, Childgender, Childage, Loved, NumChildren)$$

$$(4)\ ChildBMI = f_4(PCGWKHR, PCGChildOutdoor, FoodExp, HDBMI, HDHealth, PCGBMI, PCGAge, PCGedu, PCGwhite, Lunchpro, ActiveTime, ChildWhite, Childgender, Childage, Loved, NumChildren)$$

The definitions of the dependent variables and the independent variables in the system are presented in Table 1. The head's weekly working hours (*HDWKHR*), the head's wage rate (*HDWage*), the PCG's wage rate (*PCGWage*), and the family's non-labor income (*NlabIncome*) are the excluded variables in the system. The weekly working hours of the PCG (PCGWKHR) is used to measure the PCG's working time. The PCG's participation in market could result in less food preparation time at home and increase the consumption of food away from home. According to the Bureau of Labor Statistics, from early 1970s to early 2000s, female labor force participation rate increased from 40% to 60%. In the meaning time, USDA's food intake surveys suggest that the share of people's daily caloric intake from food away from home increased from 18 percent to 32 percent between late 1970s' and middle 1990s. Food away from home tends to contain higher calories more calories per eating occasion than food prepared at home (Lin et al., 1999, 2001; Guthrie et al., 2002). We thus hypothesize that an increase of

PCG's working time will cause an increase of children's BMI. The second reduced form equation estimates the function of joint physical activity time the PCG spends with the child using child's outdoor activity frequency with PCG (PCGChildOutdoor) as the dependent variable. Given the mixed evidence of the impacts of physical activity on children's BMI (Goran et al. 1999;Nielson Media Research 2000), we have no priori expectation about the significance and the sign of this variable in the child's BMI function. Due to the data limitation, detailed information about the amount of food consumed by individuals is not available. Hence the third reduced form equation estimates the function of the household food expenditures (FoodExp) instead of the child's food expenditures. This substitution will not prevent us from examining the impacts of food expenditure on children's BMI. A reasonable assumption we can make is that an increase in the household food expenditure will cause an increase in the child's food expenditure. As higher amounts of food consumed may imply higher energy intakes, we hypothesize a positive casual relationship between household food expenditures and children's BMI. The head's health condition (HDHealth), the head's BMI (HDBMI), the PCG's health condition (PCGHealth), and the PCG's BMI (PCGBMI) along with a set of demographic variables are included in the system as type variables *k* defined in the theoretical model to assess the impacts of biological, genetic, and socio-demographic factors on PCG's choices and children's BMI. There is a growing body of research that addresses the influence of environmental factors related to children's psychological and emotional well-being on their BMI outcomes (e.g., Puhl and Brownell 2003; Friedlander, et al., 2003; Schwimmer et al., 2003; Zametkin et al. 2004). To explore such effects, a variable *Loved* which measures the child's perception of being loved or accepted by his/her parents and peers is included. Another environmental factor included is the number of children in the household (*NumChildren*). The

variable *Lunchpro* intends to examine the effects of the National School Lunch Program (NSLP) on childhood obesity prevention. The NSLP is a federally assisted meal program that provides nutritionally balanced lunches to children each school day. We expect that the participation in the NSLP would help reduce children's BMI. Another important variable in the child's BMI function is *ActiveTime* which measures the weekly physical activity time of the child. The estimate of the effect of this variable will help advance our understanding of the relationship between physical activity and childhood obesity. The demographic variables *ChildWhite* , *Childgender* , and *Childage* describe the child's race, gender, and age.

3.2 Econometric Issues

We can express the above model in a more general form:

(7) $YB + X\Gamma = U$

Where Y is a $N \times G$ matrix of dependent variables, X is a $N \times K$ matrix of explanatory variables, and U is a $N \times G$ matrix of disturbances. N is the number of observations, and G is the number of equations. We assume i.i.d. disturbances across observations. Further, we assume zero mean matrix of U and a nonsingular covariance matrix $\Sigma \otimes I_N$. B is upper triangular. So we call it a triangular system of equations. As well known, if Σ is diagonal, which implies the special case when unobserved individual effects are not correlated across equations, the model is the recursive specification of Wold (Hausman 2003). The system can be simply estimated using OLS equation by equation. However, in real world, the disturbances across equations are usually correlated. In our case, the PCG's time allocation, food expenditures and child's BMI functions cannot be assumed independent with each other. Therefore, we may turn to SUR model (Zellner 1962). SUR allows for the correlations of error terms across equations. In such context, we can rewrite the system of equation for each observation as

(8) $y_i = X_i \beta_i + u_i$

Where $y_i = [y_{1i}, y_{2i}, ..., y_{Gi}]'$, $u_i = [u_{1i}, u_{2i}, ..., u_{Gi}]'$, and

$$X_i = \begin{bmatrix} X_{1i} & 0 & 0 & ... & 0 \\ 0 & X_{2i} & 0 & ... & 0 \\ 0 & 0 & & & \vdots \\ \vdots & & & & 0 \\ 0 & 0 & & & X_{Gi} \end{bmatrix}, \qquad \beta = \begin{bmatrix} \beta_{1i} \\ \beta_{2i} \\ \vdots \\ \beta_{Gi} \end{bmatrix}$$

So X_i is $G \times [K_1, K_2, ..., K_G]$, and $K = [K_1, K_2, ..., K_G]$. We assume the orthogonality condition $E[X_i \otimes u_i] = 0$. We define $\Omega = E[u_i u_i^{'}]$ and further assume Ω is positive definite and $E[X_i^{'} \Omega X_i]$ is nonsingular. In practice, Ω is usually not available, we need to find a consistent estimator $\widehat{\Omega}$ for Ω, i.e. $\text{plim}\, \widehat{\Omega} = \Omega$. We can have the general form of general least square (GLS) estimator or the feasible GLS estimator of β in the following form (Woodbridge 2002):

(9) $\widehat{\beta} = (\sum_{i=1}^{N} X_i^{'} \widehat{\Omega}^{-1} X_i)^{-1} (\sum_{i=1}^{N} X_i^{'} \widehat{\Omega}^{-1} y_i), \quad \widehat{\Omega} = N^{-1} \sum_{i=1}^{N} \hat{u}_i \hat{u}_i^{'}$

However, the performance of this estimator crucially depends on the assumption that $\widehat{\Omega}$ is a consistent estimator of Ω, which requires a good priori knowledge on Ω. The estimates from SUR regression can be iterated. For each iteration, new residuals will be generated which are used to construct a new weight matrix. Iteration may gain efficiency for the estimator, but again, we have to assume that the structure of Ω is correctly understood and specified. As suggested by Lahiri and Schmidt (1978), we will estimate an iterated SUR model in the analysis.

Another option we can turn to is the nonparametric approaches which are more robust to the deviation of underlying distributional assumptions and does not depend on tight functional form specifications. Based on the work of Roehrig (1988), Newey and Powell (1989), and Newey et al. (1999) regarding the estimation of triangular system of equations, Pinkse (2000)

proposes a nonparametric polynomial estimator. Consider a structural model of the following form:

(10) $y_i = g_0(x_i) + \varepsilon_i$,

Where x_i is a vector of endogenous variables. Then the reduced form equations of x_i is

(11) $x_i = \Pi_0(Z_i) + \eta_i$

Where Z_i is a vector of exogenous variables. The errors terms across equations are mutually correlated but are independent of Z_i. This setting exactly captures the structure of our model which consists of one structural equation and three reduced form equation with a non-diagonal variance matrix. Pinkse' nonparametric estimator does not impose distributional assumptions on error terms but only requires the existence of their second order moments. Furthermore, the functional forms of g_0 and Π_0 need not to be specified when using the Pinkse estimator. Hence, the estimates may be more robust to misspecification problems.

To apply Pinkse estimator, the first step is to estimate the vector Π_0 using nonparametric series regression to generate the residuals $\hat{\eta}$. The function g_0 is then estimated using nonparametric series regression of y_i on ($x_i, \hat{\eta}_i$). The series expansion of the focal *x* in a neighborhood will provide more information to smooth the observations in a local window, which ensures a better fit globally. Following Pinkse (2000), we use the commonly used Legendre polynomials for the first and second stage expansion, i.e. the jth term of the expansion around an endogenous variable *x* is constructed from the following recursion

(12) $(j+1)e_{X_{j+1}}(x) = (2j+1)\cdot x \cdot e_{X_j}(x) - j \cdot e_{X_{j-1}}(x)$

with $e_{X_0}(x) = 1/\sqrt{2}$ and $e_{X_1}(x) = 1/\sqrt{2/3}$.

Figure 1 shows the graph of Legendre Polynomials with the degree of 1 to 4.

4. Data

The data used in this study is the survey data from the national panel study of income dynamics (PSID) 2007. Since 1968, PSID has been providing longitudinal data on a wide variety of information about families' and individuals' economic and demographic characteristics, with substantial detail on income sources and amounts, employment, family composition changes, and residential location. In 1997, Child Development Supplement (CDS) data started to supplement PSID core data collection with additional information focusing on the human capital development of children in PSID families, including extensive measures of the children's home environment, children's time diaries in home and at school, school and day care environment, and measures of their cognitive, emotional and physical functioning. There have been three waves of CDS data since 1997: CDS-I 1997, CDS-II 2003, and CDS III 2007. This study uses CDS III 2007 data considering that the completed interview are more successful as the older children's have better ability to provide self-reported information in CDS III, as compared with CDS-I and CDS-II when the children were younger and a completed interview from the primary caregiver has to be considered a completed interview. After deleting missing values, our sample data resulted in 221 observations. Approximately 76% of the sampled PCG are white, and 20% are African-American with about 4% are Hispanic, Native Hawaiian or Pacific Islander, and Asian. The children in the sample are 12-19 years of age. Boys and girls account for half of the sample respectively. More importantly, the CDS collects time diaries from the sample children. These diaries provides information on how children across populations engage in a range of activities, which opens the possibility for us to examine the relationship between time spent in

physical activities and childhood obesity. In our data, children's average weekly physical activity time is about 1664 seconds. The detailed summary statistics are presented in Table 1.

5. Results

5.1 Parametric ISUR Estimation

Iterated seemingly unrelated regression (ISUR) estimates of the reduced form equations are reported in Table 2. In Column 2 of Table 2, the coefficient estimates suggest that the amount of time that a PCG inputs into market production to earn wage is influenced by her wage rate. As the wage rate increases, she works shorter hours. Although discussion of the reasons behind the reduction of working hours due to wage increase is beyond the scope of this paper, existing studies do suggest that wage increases could reduce working mothers' hours worked (e.g. Sabia 2007). The reduction could be both voluntary and involuntary. For example, Villa (1993) suggests that negative relationship between weekly hours worked and the gross hourly wage rate is due to the provision of fringe benefits. Further labor research needs to be done to examine the phenomenon. The household head's wage rate is negatively correlated with the PCG's working hours. The significant and negative coefficient of the household head's wage rate suggests that higher wage rate of the household head would influence the PCG to decrease her working hours. This may be attributed to the effects of higher income brought by the head which reduces the needs for the PCG to earn extra income for the household. An interesting finding is that if a PCG believes that an employed mother can establish as warm and secure a relationship with her children as a mother who is not employed, she will put more hours in market instead of in family. This results is indicated by the significant ($\alpha = 0.01$) and positive coefficient of the variable EmpMom which is a dichotomous variable indicating if a PCG holds that belief. Moreover, the number of children in a family is another influential factor that determines a

PCG's working hour input. The more children that a family has, the less hours a PCG will work for wages. This is an expected result, as more children requires the PCG to spend more time on parenting at home and thus indicates a need for less market participation.

The estimates of PCG's outdoor activity involvement function are reported in Colum 4 Table 2. As the estimates suggest, a PCG's health condition affects the frequency that she participates in her children's outdoor activities. Better health status could lead to higher participation frequency. Furthermore, higher BMI of a PCG is shown to lower the frequency of her involvement in children's outdoor activities. The outdoor activities include a broad range of physical activities, such as gymnastics, sports, cheerleading, art and crafts, dance, family groups, religious services, and etc. These findings are not surprising as physical conditions or functional impairments would affect people' capability and willingness to engage in outdoor activities. A PCG with less healthy status would face more physical challenges and limitations in outdoor activities which in turn cause her to choose to participate in these activities less frequently. The estimates also suggest the influence of a PCG's wage rate on her outdoor activity involvement with children. An increase of wage rate would increase the cost for a PCG to spend time with children in outdoor activities and thus may reduce the PCG-child outdoor activity involvement frequency. The negative coefficient of the PCG's wage rate in outdoor activity involvement function indicates this trend. Moreover, the results suggest the impact of a head's working hours on a PCG's participation in children's outdoor activities. The more time the head works, the less frequently that the PCG will play in outdoor activities with the children. This finding reflects the time constraint that a PCG faces in parenting when the head is out for work.

The obstacle posed by data limitation prevents us from analyzing detailed diet composition to investigate household energy intake patterns. For this reason, we use

household food expenditures to estimate energy intake. One caveat of this proxy is that energy-dense nutrient-poor foods may be cheaper than less energy-dense foods, which allows for a higher energy intake at a lower cost. Consequently, it is possible that high food expenditures may not necessarily reflect high energy consumption but otherwise instead. Drewnowski and Specter's (2004) study shows a positive relationship between a household's energy intake and its diet costs in typical American diets. Hence, household food expenditures may still be able to serve as reasonable estimates for household energy intake. The food expenditure function estimates in column 5 Table 2 suggest that economic factors play a major role in determining how much a household would spend on food since the head's wage rate is the determinant of the amount of the food expenditures of a household.

Table 3 presents the estimates of the Child's BMI production function. A PCG's working time and participation in children's outdoor activities seem to have no significant impacts on children's BMI. These results do not support You and Davis's (2010) finding that PCG's time allocation choices would affect children's BMI. Regarding food expenditure, the confounding effects of energy cost may have caused the impact of food expenditure on children's BMI to be undetectable. Less energy-dense food, such as fruits and vegetables, usually carry higher price tags. Therefore, an increase in food expenditure may possibly reflect an energy intake decrease resulted from healthier food purchasing instead of an energy intake increase. Without information to document the detailed diet composition, we are unable to distinguish these effects. An interesting and notable finding is that parents' BMI significantly affect their children's BMI. Although biological factors may not be able to explain the rapid increase of obesity, parents' BMI do influence their children's BMI through their dietary behaviors and family environment. PCG's education also impacts children's BMI. It appears that more education of a PCG is

associated with lower child BMI. It's possible that a PCG with more education will be able to make healthier food choices which would help lower children's BMI. Interestingly, the estimates do not suggest the significant impact of children's active leisure time on their BMI. It was hypothesized that more active leisure time would cause more energy expended. Therefore we expect to observe a significant and negative impact of active leisure time on children's BMI. However, the estimates do not suggest this trend.

5.2 Semi-parametric Estimation

Considering the system of equations includes a large number of explanatory variables, if we use fully nonparametric specification, the curse of dimensionality (i.e. the problem caused by the exponential increase in the number of extra dimensions added into the function space) would cause estimation difficulty and generate unacceptably large variances of estimates. Hence we take a semi-parametric specification which consists of an unknown nonparametric function of endogenous variables and additive parametric components:

$$\begin{aligned} ChildBMI &= \Pi_0(PCGWKHR, PCGChildOutdoor, FoodExp) \\ &\quad + f_0(, HDBMI, HDHealth, PCGBMI, PCGage, PCGedu, PCGwhite, \\ &\qquad Lunchpro, ActiveTime, ChildWhite, Childgender, Childage, Loved, \\ &\qquad NumChildren) \end{aligned}$$

$$\begin{aligned} PCGWKHR &= \Pi_1(PCGWage, HDWKHR, HDWage, NlabIncome) \\ &\quad + f_1(HDBMI, HDHealth, PCGBMI, PCGHealth, EmpMom, PCGage, \\ &\qquad PCGedu\ PCGwhite, Lunchpro, ActiveTime, ChildWhite, Childgender, \\ &\qquad Childage, Loved, NumChildren) \end{aligned}$$

$$PCGChildOutdoor = \Pi_2(PCGWage, HDWKHR\ , HDWage, NlabIncome)$$
$$+\ f_2(\ HDBMI, HDHealth, PCGBMI, PCGHealth,\ EmpMom, PCGage,$$
$$PCGedu\ PCGwhite, Lunchpro, ActiveTime, ChildWhite, Childgender,$$
$$Childage,\ \ Loved, NumChildren)$$

$$FoodExp = \Pi_3(PCGWage, HDWKHR\ , HDWage, NlabIncome)$$
$$+\ f_3(\ HDBMI, HDHealth, PCGBMI, PCGHealth,\ EmpMom, PCGage,$$
$$PCGedu\ PCGwhite, Lunchpro, ActiveTime, ChildWhite, Childgender,$$
$$Childage,\ \ Loved, NumChildren)$$

Where Π_1, Π_2, Π_3 are unknown functions which are expanded using Legendre polynomials series, while f_1, f_2, f_3 are additive linear functions. Another concern in the estimation is the orders of the polynomial in the first stage and in the second stage. The orders in the stage one and the stage two estimations can be different. It is not necessarily true that higher order smoothing will perform better than lower order smoothing. Systematic method for deciding optimal length of polynomials in the first stage and the second stage is not available in existing literature. Monte Carlo simulation results (Pinkse 2000) suggest that choosing 2 and 4 in the first and second regression stage separately would be good choices in terms of minimizing the mean squared errors. We therefore use the length of 2 and 4 for our first stage and second stage Legendre polynomial regressions respectively.

Table 4 and Table 5 report the results from the Pinkse (2000) semi-parametric estimation. In contrast with the ISUR estimates, the effects of PCG's wage rate and the head's wage rate on PCG's working hour choice become insignificant. The consistent findings are the impacts of a PCG's belief about the role of working mom and the number of children in a household on the PCG's working time decision. The results suggest that if the PCG believes that an employed mother can establish as warm and secure a relationship with her children as a mother who is not

employed, she will increase about 2 hours in a working week. Moreover, one more child increase in a family may cause the PCG to reduce about 2 hours working time per week ($\alpha = 0.01$). It can be reasoned that the need of child care plays an important role when the PCG decides how much time to work in market.

The estimates of PCG's outdoor activity involvement function in column 4 Table 4 also imply that a PCG's health condition can significantly influence the frequency that she participates in children's outdoor activities. This finding is consistent with the result from ISUR estimation, which suggests the robust effect of the health status of a PCG on her participation decision.

Household food expenditures are more associated with economic factors. The estimates in column 6 Table 4 suggest that a head's wage rate is the most influential factor of a household's food expenditures. Higher wage rate of the head would lead to higher spending on food. Ceteris paribus, on average, a dollar increase in a head's hourly wage rate may lead to 11 dollar increase in the household's monthly food expenditures ($\alpha = 0.01$). In line with the results of ISUR estimation, this finding suggests the impacts of income on food expenditures because the head is the primary income earner of a household and his wage rate largely determines the household income.

Table 5 reports the semi-parametric estimates from the child's BMI function. As in the ISUR estimation, the semi-parametric estimates do not suggest significant impacts of a PCG's working hours, the frequency of the child's outdoor activity with PCG, and household food expenditures on the child's BMI. The loose relations between these PCG choices and the child's BMI reflects the complexity of parenting impacts as they are related to children's dietary intake and energy expenditure. Notably, the semi-parametric estimates support the findings from ISUR

estimation that parents' BMI significantly impact children's BMI. High BMI of parents could cause high BMI of their children, indicating that obese parents tend to have obese children. A plausible explanation behind this finding is that parents' energy intake and energy expense patterns which determine their own BMI may also indirectly affect their children's BMI, such as food and beverage preferences, exercise habits, and etc. Hence, the causes for adult obesity increase could also contribute to the rapid increase in childhood obesity. Furthermore, parents with higher BMI may be lack of efficient means for their own weight control, which in turn may lead to less effective control over children's weight gain. In line with the findings from ISUR, the results indicate that the number of children in a household could also influence children's BMI. One more child increase in a family may lead to about a 0.8 increase in children's BMI. Quality of parenting and dietary intakes related to the family size may be a possible cause for such relation. As in ISUR estimation, the semi-parametric estimates suggest the insignificant impacts of physical activity time on children's BMI. Causal relationship between physical activity and childhood obesity cannot be established. Our findings add to the growing body of controversies about the relation between physical activity and body weight in literature (Robinson et al. 1993; DeLany et al. 1995; Treuth et al.1998; Goran et al.1999; Sallis 2003; Vandewate et al. 2004).

6. Semi-parametric and Parametric Model Comparison

How to choose an econometric model over others has always been a difficult task in applied research. There is a wealth of criteria that can be used to measure the model performance and adequacy, such as the variance explained by the model, error behaviors, robustness to the assumption deviations and misspefications, and other visual diagnostics. However, within-sample exploration of these attributes may not be as informative as researchers usually think for

testing the model performance. White (2000) points out that the observed good performance of a model could only be due to luck instead of superior fit.

There is a trend in recent literature that advocates the using out-of-sample predictive ability to guide model choices (Corradi and Swanson 2007). Although such methods have become common in time-series research, cross-sectional applications are still rare. Racin and Parmeter (2009) propose an approach using sample-splitting for out-of sample prediction tests in cross-sectional studies. Their approach overcomes limitations of the popular predictive ability time-series tests, such as the reliance on only one split of the data and the need to have a sufficiently large hold-out sample to possess adequate test power, and provides practical metric for model choice based on predictive performance on independent and identically-distributed data. Suppose we have two models, Model A and Model B. Following Racin and Parmeter (2009), we could apply the proposed measure as:

(1). Use Bootstrap without replacement to resample original data set S times to form S resamples and index these resamples as $\left\{X_i^s, Y_i^s\right\}_{i=1}^{n}$;

(2). For each resample, we equally split the sample. Then we use the first half to form a training sample, $z_s^1 = \left\{X_i^s, Y_i^s\right\}_{i=1}^{n_1}$ and the second half to form the evaluation sample $z_s^2 = \left\{X_i^s, Y_i^s\right\}_{i=1}^{n_2}$

(3). Fit Model A and Model B on z_s^1 to obtain the regression models $\hat{g}_{z_s^1}^{A}$ and $\hat{g}_{z_s^1}^{B}$ for Model A and Model B respectively.

(4). Obtain predicted values using z_s^2 and compute the Average Squared Prediction Error (ASPE) for each model as: $ASPE_s^A = \frac{2}{n}\sum_{i=n/2+1}^{n}(y_i^s - \hat{g}_{z_s^1}^{A}(X_i^s))^2$, $ASPE_s^B = \frac{2}{n}\sum_{i=n/2+1}^{n}(y_i^s - \hat{g}_{z_s^1}^{B}(X_i^s))^2$

(5). Use the S draws to construct the empirical cumulative distributions of $\left\{ASPE_s^A\right\}_{s=1}^S$ and $\left\{ASPE_s^A\right\}_{s=1}^S$ respectively which can be used for statistical inferences.

Based on this algorithm, we test the performance of the semi-parametric model and iterated SUR model in terms of their ASPE using S=5000, S=10000, and S=50000 to avoid the random consequences of too few splits. Table 7 reports the P-value in each scenario. The test result suggests that the semi-parametric model is preferred to parametric model at $\alpha = 0.01$ level when S = 5000. As we increase the number of splits, this trend does not alter, indicating the stochastic dominance of the semi-parametric model over the iterated SUR model. Figure 2 presents the empirical distribution functions of ASPE for each model. It presents a visual demonstration of the performance of different model specifications based on ASPE. There is a trend in Figure 2 that the gap between the empirical CDF of the two models tends to narrow when the number of splits increases from 5000 to 10000. The tendency continues when we increase the number of splits from 10000 to 50000. This trend suggests the asymptotic equivalency of the two estimators.

However, ASPE based tests are just indicators for relative predictive ability among alternative specifications. These tests are not about finding a "true" model which describes the true underlying data generating process but only provides a means to discriminate among models. Although the comparison indicates relatively better performance of the semi-parametric model, estimates from both parametric and semi-parametric approaches should be used jointly to examine the robustness of the results to model variations and to make more informative conclusions. Indeed, there is no large gap between the results from iterated SUR and the results from the semi-parametric polynomial estimation.

7. Conclusion

The main objective of this study is to examine the impacts of PCG's time allocation and food expenditure choices on children's BMI using nationally representative survey data. In contrast to previous studies, our results do not suggest the significant impacts of PCG's labor force participation choices, involvement in children's outdoor activity, and household food expenditures on children's BMI. Interestingly, the estimates from both iterated SUR and semi-parametric polynomial estimations indicate that parents' BMI significantly influence children's BMI. Obese parents tend to have obese children. This result cannot be solely attributed to the genetic influences as gene alone cannot explain the abrupt increase in childhood obesity. Furthermore, physical activity appears to have weak correlation with children's BMI. More physical activity time does not necessarily lead to lower BMI of children. These results reflect the complexity of the causes of childhood obesity. The second objective of this study is to investigate the applicability of parametric and semi-parametric approaches to estimate a simultaneous triangular system of equations, as the latter do not depend on restrictive distributional assumptions and tight functional forms. We compare the performance of the semi-parametric model and the iterated SUR model in terms of their ASPE. The ASPE tests indicate relatively better performance of the semi-parametric model. However, we do not observe dramatic changes in the results between the two models. The estimates from parametric and semi-parametric estimations are quite consistent, implying the robustness of our findings. In Summary, our results suggest that improving parent's behavior related to adult BMI reduction may also help lower their children's BMI. Although this paper does not reveal concrete evidences of what may have caused the rapid increase of childhood obesity, it does show that parents play a central role in fighting the epidemic.

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Figure 1: Legendre Polynomial

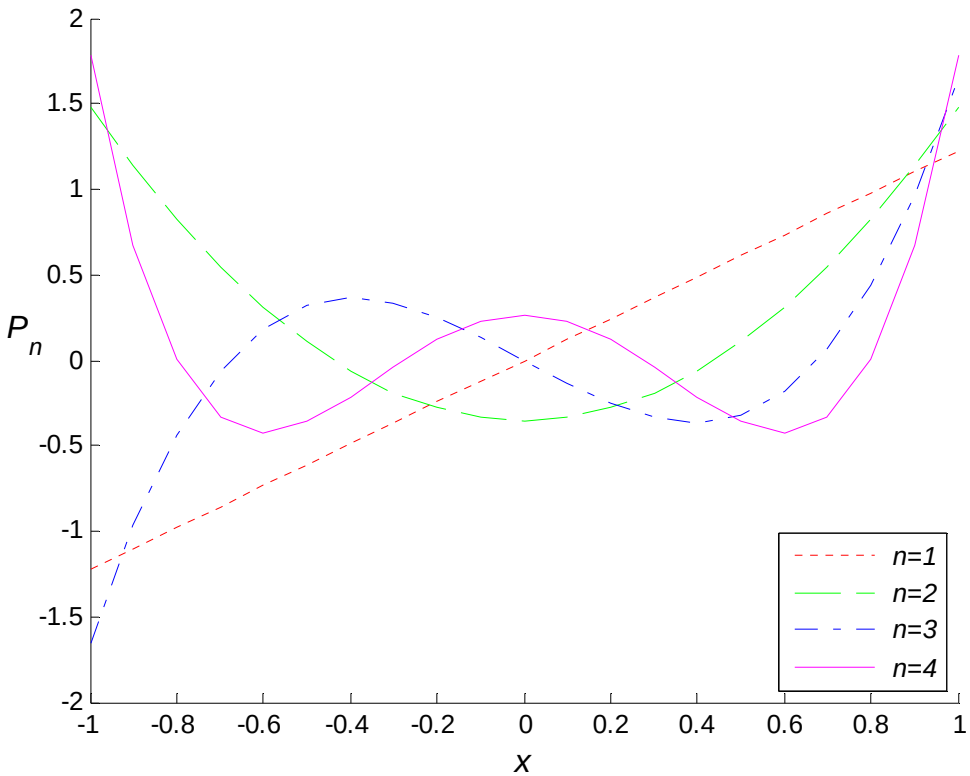
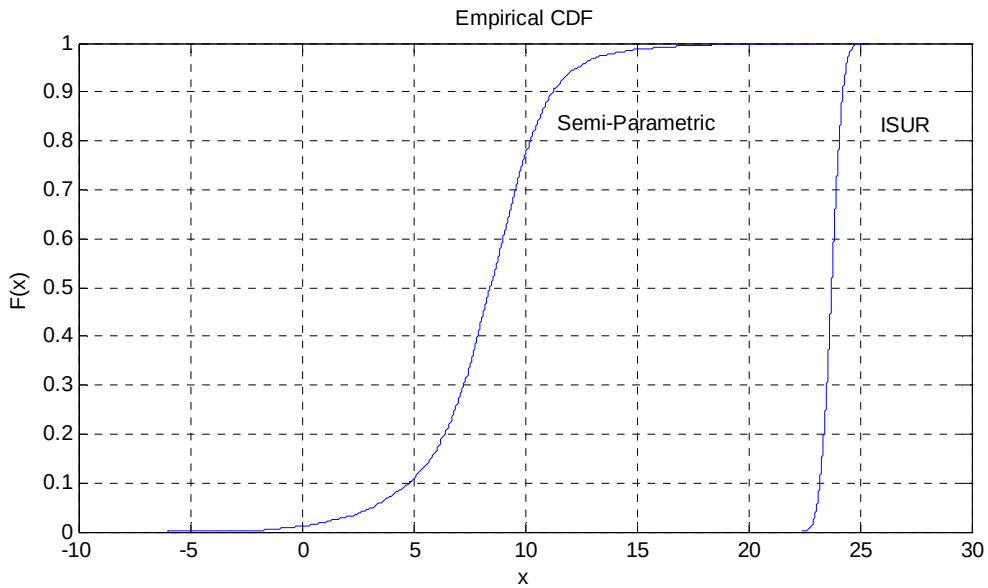


Figure 2: Empirical Cumulative Distributions of ASPE (S = 5000, 10000, and 50000)



Splits = 5000

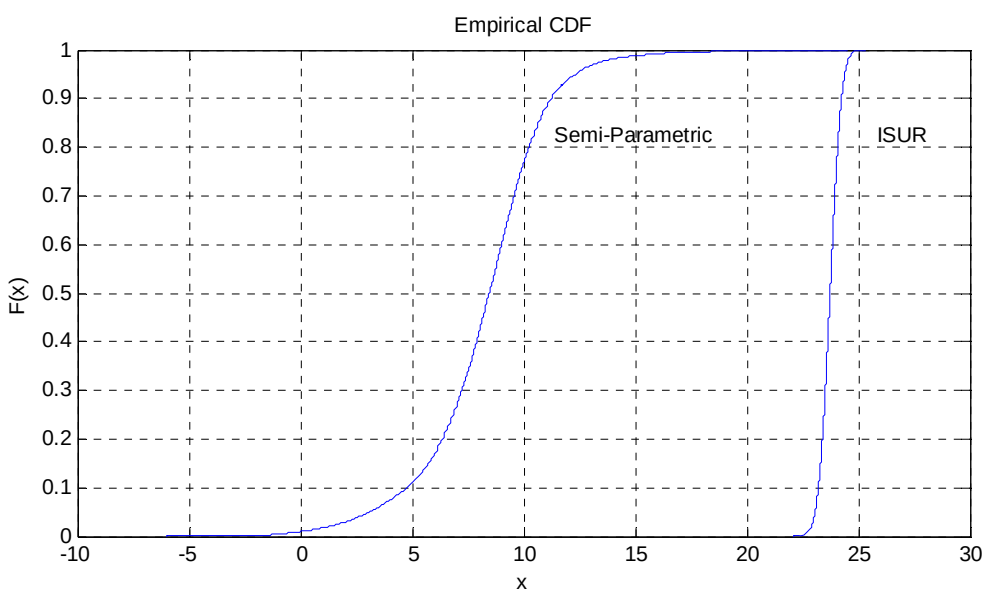


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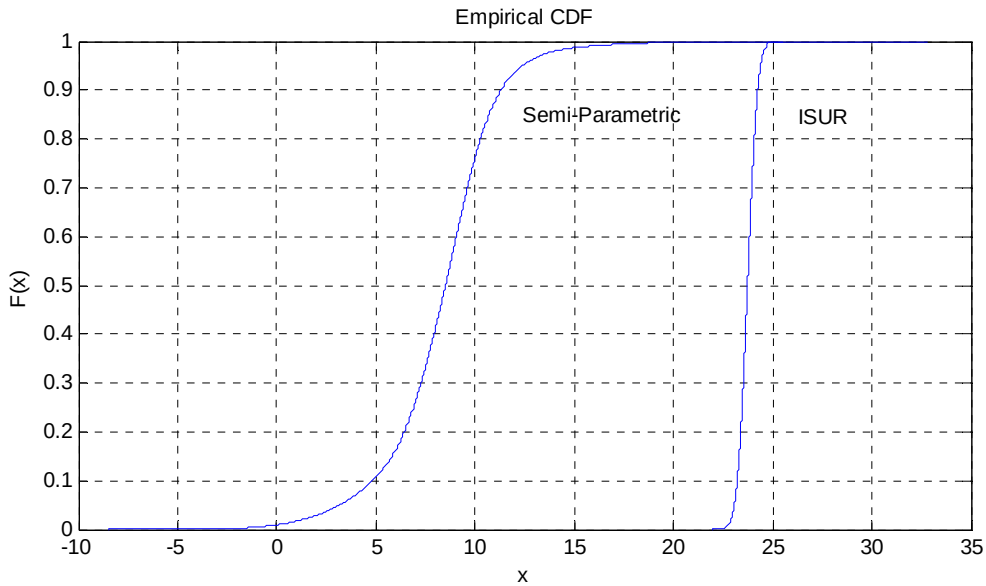
Figure 2: Empirical Cumulative Distributions of ASPE (S = 5000, 10000, and 50000) -continued



Splits = 50000

Table 1: Variable Description (N=221)

Variables	Definition	Scale	Mean	S.D.	Min	Max
Dependent						
PCGWKHR	Weekly working hours of PCG	Continuous	37.24	17.99	1.00	100.00
PCGChildOutdoor	Child's outdoor activity frequency with PCG	Categorical 1 = Never 2 = A few times a year or less 3 = About once a month 4 = A few times a month 5 = About once a week 6 = Several times a week 7 = At least once a day	3.88	1.49	1.00	7.00
FoodExp	Monthly food expenditures of a household	Continuous	761.81	303.09	310	2200
ChildBMI	BMI of the child	Continuous	23.72	5.97	15.2	48.7
Independent						
PCGwage	Wage rate of PCG per hour	Continuous	18.59	11.74	0.83	62.03
EmpMom	If the PCG agrees that an employed mother can establish as warm and secure a relationship with her children as a mother who is not employed	Categorical 1 = Strongly disagree 2 = Disagree 3 = Agree 4 = Strongly agree	3.24	0.70	1.00	4.00
PCGBMI	PCG's BMI (weight in pounds *703)/(height in inches)^2	Continuous	27.77	6.74	15.94	54.86

Variables	Definition	Scale	Mean	S.D.	Min	Max
PCGHealth	PCG's health status	Categorical 1 = Excellent 2 = Very good 3 = Good 4 = Fair 5 = Poor	2.24	0.95	1.00	5.00
PCGage	Age of PCG	Continuous	42.96	6.03	29	58
PCGedu	Completed years of education of PCG	Continuous	13.79	2.42	0	17
PCGwhite	If the PCG is white	Dummy	0.76	0.43	0.00	1.00
HDWKHR	Weekly working hours of head	Continuous	46.30	11.53	9	91
HDwage	Wage rate of head per hour	Continuous	28.55	20.24	2.57	113.32
HDBMI	Head's BMI (weight in pounds *703)/(height in inches)2	Continuous	28.75	4.70	19.86	46.11
HDHealth	Household head's health status	Categorical 1 = Excellent 2 = Very good 3 = Good 4 = Fair 5 = Poor	2.17	0.96	1.00	5.00
NumChildren	Number of children in the family	Continuous	1.82	0.92	1.00	7.00
Lunchpro	If the child eats a complete hot lunch offered at school	Dummy 1 = Yes ; 0, otherwise	0.64	0.48	0.00	1.00
Loved	If the child feels or complains that no one loves him/her	Dummy 1 = Yes ; 0, otherwise	0.82	0.39	0.00	1.00
Childwhite	If the child is white	Dummy	0.79	0.41	0.00	1.00

Variables	Definition	Scale	Mean	S.D.	Min	Max
		1= Yes ; 0, otherwise				
ActiveTime	Child's active leisure, sports and exercise time in weekdays and on weendends (in Seconds)	Continuous	1663.98	4105.10	0	31020
Childgender	Gender of the child	Dummy 1 = boy ;0 = girl	0.51	0.50	0.00	1.00
childage	Age of the child	Continuous	15.38	1.84	12.08	19.09

Table 2: ISUR Estimation of Reduced From Equations

	PCGWKHR Equation		PCGChildOutdoor Equation		FoodExp Equation	
Variables	Coefficients	Std.Err.	Coefficients	Std.Err.	Coefficients	Std.Err.
Constant	23.87	13.33	10.52	1.58	305.88	320.70
PCGWage	-0.21***	0.08	-0.02*	0.01	2.74	1.87
HDWKHR	0.11	0.07	-0.02**	0.01	2.44	1.62
HDWage	-0.15***	0.04	0.00	0.01	4.92***	1.02
NLabIncome	0.00	0.00	0.00	0.00	0.00	0.00
PCGBMI	0.02	0.14	-0.02	0.02	-1.47	3.39
HDBMI	0.17	0.19	-0.05**	0.02	0.98	4.54
HDHealth	-0.98	0.93	0.11	0.11	29.29	22.36
PCGHealth	-1.11	0.96	-0.23**	0.11	15.12	23.18
EmpMom	3.24***	1.19	0.02	0.14	20.04	28.69
NumChildren	-2.02**	0.98	0.00	0.12	16.04	23.68
PCGage	0.10	0.17	0.01	0.02	0.60	4.01
PCGedu	0.43	0.41	-0.11**	0.05	-3.71	9.92
PCGwhite	-4.74	3.37	0.25	0.40	118.80	81.00
Loved	-2.11	2.01	0.41	0.24	46.21	48.30
Lunchpro	4.96***	1.85	-0.02	0.22	20.35	44.35
ActiveTime	0.00	0.00	0.00	0.00	0.00	0.00
Childwhite	1.18	3.25	-0.16	0.39	-12.97	78.28
Childgender	-1.23	1.73	-0.21	0.21	-20.09	41.63
Childage	-0.17	0.46	-0.17***	0.05	-8.62	10.98
R-Squared	0.25		0.18		0.19	
Chi-Squared	74.57		48.69		53.85	

Notes: (*) denotes statistical significance at least at a=0.1. (**) denotes statistical significance at least at a=0.05. (***) denotes statistical significance at least at a=0.01.

Table 3: ISUR Estimation of Children's BMI function

Variables	Coefficients	Std.Err.
Constant	-9.31	6.84
PCGWKHR	0.03	0.03
PCGChildOutdoor	0.33	0.26
FoodExp	0.00	0.00
HDHealth	0.78*	0.44
PCGHealth	0.01	0.46
PCGBMI	0.17***	0.07
HDBMI	0.18**	0.09
PCGage	0.13*	0.08
NumChildren	0.83*	0.47
PCGedu	-0.03	0.18
PCGwhite	1.71	1.60
EMpMom	0.44	0.57
Loved	-0.65	0.96
Lunchpro	1.32	0.86
ActiveTime	0.00	0.00
Childwhite	-2.43	1.52
Childgender	0.52	0.82
Childage	0.93***	0.22
R-Squared	0.19	
Chi-Squared	85.14	

Notes: (*) denotes statistical significance at least at a=0.1. (**) denotes statistical significance at least at a=0.05. (***) denotes statistical significance at least at a=0.01.

Table 4: Semi-Parametric Polynomial Estimation of Reduced Form Equations

	PCGWKHR Equation		PCGChildOutdoor Equation		FoodExp Equation	
Variables	Coeff.	S.E.	Coeff.	S.E	Coeff.	S.E.
Constant	35.6096	14.9457	10.3239	1.8975	60.0597	384.1516
PCGwage	-0.3088	0.2515	0.0467	0.0319	5.1350	6.4653
HDWKHR	-0.0151	0.3082	-0.0306	0.0391	11.2750	7.9219
HDWage	-0.0336	0.1394	-0.0043	0.0177	11.7314***	3.5823
NLabIncome	0.0003	0.0000	0.0000	0.0000	-0.0002	0.0011
PCGBMI	0.1246	0.1389	-0.0266	0.0176	-1.6338	3.5706
HDBMI	0.0803	0.1871	-0.0491**	0.0238	0.5528	4.8093
HDHealth	-0.2119	0.9218	0.0968	0.1170	32.3842	23.6929
PCGHealth	-1.2443	0.9421	-0.2235*	0.1196	14.5626	24.2150
EmpMom	2.2194*	1.1791	0.0568	0.1497	19.2197	30.3059
NumChildren	-1.9696**	0.9643	-0.0129	0.1224	12.8456	24.7848
PCGage	-0.0765	0.1669	0.0127	0.0212	-0.4383	4.2886
PCGedu	0.2219	0.4096	-0.1053**	0.0520	-7.4043	10.5281
PCGwhite	-4.5752	3.2941	0.2593	0.4182	115.8031	84.6686
Loveid	-1.0427	1.9823	0.3987	0.2517	33.3247	50.9519
Lunchpro	4.0893**	1.8216	0.0299	0.2313	29.1662	46.8208
ActiveTime	0.0000	0.0002	0.0000	0.0000	0.0034	0.0051
Childwhite	1.9797	3.1910	-0.1804	0.4051	-25.3329	82.0186
Childgender	-1.9951	1.7113	-0.2227	0.2173	-31.3686	43.9872
Childage	-0.4238	0.4504	-0.1585***	0.0572	-5.8972	11.5762
pcgwage2	-0.0009	0.0023	-0.0006*	0.0003	-0.0201	0.0589
hrhd2	0.0006	0.0016	0.0001	0.0002	-0.0465	0.0416
wagehd2	-0.0004	0.0007	0.0000	0.0001	-0.0381**	0.0187
nlabincome2	0.0000	0.0000	0.0000*	0.0000	0.0000	0.0000
R-Squared	0.3632		0.2039		0.2139	
F-value	4.88		2.19		2.33	

Notes: (*) denotes statistical significance at least at a=0.1. (**) denotes statistical significance at least at a=0.05. (***) denotes statistical significance at least at a=0.01.

Table 5: Semi-parametric Polynomial Estimation of Child' BMI Function

Variables	Coefficients	Std.Err.
Constant	-15.91	16.11
PCGWKHR	0.03	0.11
PCGChildOutdoor	2.16	2.36
FoodExp	0.00	0.01
HDHealth	0.85*	0.49
PCGHealth	0.06	0.55
PCGBMI	0.18**	0.07
HDBMI	0.19*	0.11
PCGage	0.11	0.08
NumChildren	0.82*	0.50
PCGedu	0.02	0.24
PCGwhite	1.47	1.73
EMpMom	0.38	0.64
Loved	-0.67	1.14
Lunchpro	1.02	0.94
ActiveTime	0.00	0.00
Childwhite	-2.33	1.61
Childgender	0.78	0.91
Childage	0.97***	0.32
pcghr3	0.00	0.00
pcghr4	0.00	0.00
freqout3	-0.02	0.04
freqout4	0.00	0.00
foodexp3	0.00	0.00
foodexp4	0.00	0.00
resid1	-0.05	0.08
resid2	-0.66	1.28
resid3	0.01	0.00
R-Squared	0.27	
F(27,193)	2.68	

Notes: (*) denotes statistical significance at least at a=0.1. (**) denotes statistical significance at least at a=0.05. (***) denotes statistical significance at least at a=0.01.

Table 6: ASPE Tests for Model Discrimination (null: the ISUR model has equal or improved predictive accuracy compared to semi-parametric model)

Splits	S = 5000	S = 10000	S = 50000
p-value	0.000	0.002	0.0006