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**Are National School Lunch Program Participants More Likely to be Obese?
Dealing with Identification**

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*Selected Paper prepared for presentation at the Agricultural & Applied Economics
Association's 2012 AAEA Annual Meeting, Seattle, Washington, August 12-14, 2012*

Abstract: The National School Lunch Program (NSLP) has been criticized for providing high calorie lunches to over 31 million school-age students. With nearly 17 percent of children considered obese, the relationship between NSLP participation and childhood obesity has been studied extensively without conclusive evidence. This paper presents a review of the literature thus far and examines identification issues when estimating the average treatment effect or local average treatment effect of the NSLP. Using data from the National Health and Nutrition Examination Survey (NHANES), the author finds that when restrictive parametric assumptions are removed, participation in the NSLP reduces the probability of being obese in school age children.

JEL: C14; I38; Q18

Keywords: National School Lunch Program; Obesity; Regression Discontinuity; Monotone Instrumental Variable

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I. Introduction

Childhood obesity has become a growing health concern in the United States, with nearly 17 percent of two- to nineteen-year-old children considered obese (Ogden & Carroll, 2010). With this comes a greater risk of health problems such as Type 2 diabetes, high blood pressure, and high cholesterol (Ogden & Carroll, 2010). Although the source of the obesity epidemic is debated in the literature with some authors pointing to a sedentary lifestyle (Blair & Brodney, 1999) and genetics (Comuzzi & Allison, 1998) as causes, most researchers cite increased consumption as the main culprit (Chandon & Wansink, 2007a and 2007b; Hill & Peters, 1998). There is also strong evidence that overweight¹ or obese children are more likely to be overweight or obese as adults (U.S. Department of Health and Human Services, 2001). These findings demonstrate the urgent need to improve childhood nutrition and take action to reduce the rate of childhood obesity.

One way to achieve these aims may be through the National School Lunch Program (NSLP) that provides lunch for over 31 million school-age students at a cost of \$10.8 billion (U.S. Department of Agriculture, 2011). The NSLP was established in 1946 with the dual-goal to reduce government commodity surpluses while providing low-income children a nutritious meal (Ralston et al., 2008). Since then, it has become one of the largest nutrition-assistance programs in the United States, with over eighty percent of all primary and secondary schools participating. The current program provides free and reduced-cost lunches for income-eligible students, as well as minimally subsidizing paid lunches for students that are income-ineligible. Students with a household income of 130 percent of the poverty line or less are eligible for the free lunch. Students with household incomes between 130 percent and 185 percent of the poverty line are

¹ Children that are obese have a Body Mass Index (BMI) above the 95th percentile. A child is overweight if his or her BMI falls between 85th and 95th percentile and is also said to be at risk of obesity.

eligible for the reduced-price lunch. Students with household incomes over 185 are income-ineligible but may purchase a “full-price” lunch.² Thus the nutritional standards of the NSLP may impact children of various socio-demographic backgrounds.

While all children are at risk of obesity if calorie consumption and inactivity are left unchecked, low-income minorities are at greater risk than their counterparts (Ogden & Carroll, 2010). This is particularly troubling because recent studies have found a positive correlation between participation in the NSLP and child weight (Millimet et al., 2010; Schanzenbach, 2009). The correlation may be due to selection bias into the program or because of increased fat consumption of program participants relative to non-participants at lunch. A 2004-2005 School Nutrition Dietary Assessment (SNDA) conducted by the Food and Nutrition Service of the USDA found that less than one-third of schools were serving meals in compliance with the *Dietary Guidelines for Americans*. These guidelines require no more than thirty percent of calories to come from fat and less than ten percent of calories to come from saturated fat (Ralston et al., 2008). Gleason and Suitor (2003) estimate that NSLP participants on average consumed ninety-five percent more sodium than recommended while non-participants consumed eighty-eight percent more sodium than recommended. The authors also find that NSLP participants consume more dietary fat as a percentage of calories. Although the levels of nutrient deficiencies vary slightly across studies, the majority of the research concedes that NSLP participants consume more fats and sodium than non-participants, which may lead to higher rates of overweight and obesity.

These findings highlight the difficulty in determining a causal relationship between the school lunch program and childhood obesity. This paper examines parametric and non-parametric approaches to identifying the average treatment effect (ATE) and local average

² In 2011, the poverty line for a family of four was \$22,340 (U.S. Department of Agriculture, 2011).

treatment effect (LATE) of participation in the NSLP on the rate of obesity. Using data from the National Health and Nutrition Examination Survey (NHANES), we find estimation of the effect depends on the model: OLS regression and bivariate probit model find a positive effect of participation in the school lunch program on the likelihood of being obese. Contrarily, regression discontinuity design and nonparametric bounds estimation procedures identify a negative, but insignificant, effect of participation on the likelihood of being obese. The positive effect of the NSLP on obesity is removed when nonparametric estimation is used.

II. Literature Review

Identification issues are inherent in many economic problems, and estimating the relationship of the NSLP on childhood obesity is no exception. To begin, selection into the NSLP is not random; many of the same populations at higher risk for obesity are more likely to choose to participate in the NSLP (Currie, 2003; Ogden & Carroll, 2010). Furthermore, participants are not a homogenous group. Unlike most government programs providing food for low-income children, any child can participate in the NSLP regardless of income. However, due to the three-tier pricing structure, all participants do not face the same prices. While all previous studies have controlled for income when assessing the impact of participation on childhood obesity, most have not distinguished between participants receiving free or reduced price lunches (referred to as income-eligible students) and participants receiving a full price lunch (income-ineligible students). Two exceptions include Gunderson et al. (2012), who analyzes the impact for income eligible students and Schanzenbach (2009), who analyzes the effect of participation for income-ineligible students.

There has been a significant amount of research about the NSLP within the economics literature as well as the nutrition science literature. Until recently, results have been descriptive

in nature and have not considered the effects of non-random selection into the program. Current analyses of the relationship between the NSLP and nutritional outcomes (including the rate of obesity) use a variety of methods to control for selection on unobservables, including fixed effects (Gleason & Sutor, 2003), two-step Heckman procedures (Long, 1991), regression discontinuity (Schanzenbach, 2009), and propensity score matching (Campbell et al., 2011). Instrumental variables have, for the most part, been rejected due to minimal predictive power (Bhattacharya et al., 2004).

Using data from the National Health and Nutrition Examination Survey (NHANES) 1999 to 2006, Campbell et al., (2011) estimate the average treatment effect of the treated (ATET) using propensity score matching. Instead of looking at the effect of participation on weight, the authors look at specific nutritional intakes such as fat, sodium, and vitamins and find that students participating in the NSLP five days a week report consuming more Vitamin A, calcium, protein, and fat at lunch than non-participants. These results support previous research by Gleason & Sutor (2003) using fixed effects model. Campbell et al. also determine that these increases in nutrients come from consuming a higher-quantity diet (not a higher-quality diet) than non-participants at lunch. The differences between participants and non-participants' food consumption at breakfast and dinner are insignificant. These results suggest that participation in the NSLP may increase the probability of being obese through consuming larger quantities of food at lunch.

Schanzenbach (2009) uses panel data from the Early Childhood Longitudinal Study—Kindergarten Cohort (ECLS-K) to assess the causal effect of the NSLP on obesity. The author separates individuals into risk categories depending on their weight upon entering kindergarten and observes that income-ineligible NSLP participants are 1 to 2 percentage points more likely to

be obese by end of first grade. Additionally, taking advantage of the sharp income-eligibility cutoff of 185 percent, Schanzenbach uses regression-discontinuity design (RD) to observe that income-eligible students are more likely to be obese than income-ineligible students. Due to the limitations of RD, this result only holds for students with household income around 185 percent. Using the same dataset, Millimet et al. (2010) assess the impact of both the NSLP and the School Breakfast Program (SBP). They find similar results to Schanzenbach, even though their sample includes income-eligible and ineligible students. Millimet et al. then use a bivariate probit model to estimate the impact of positive selection into the SBP. When controlling for positive selection, the authors find that the school lunch program contributes to obesity rates while the breakfast program does not.

Another way to account for endogeneity in treatment not captured by covariates is by computing bounds on average treatment effect. Gunderson et al. (2012) calculate bounds on average treatment effect of the NSLP on three negative health outcomes: self-reported poor health, household food insecurity, and obesity. The data are collected from NHANES 2002 to 2004 and the sample is limited to income-eligible students. The authors use a monotone instrumental variable assumption that each outcome is non-increasing with income such that non-participants have weakly lower outcomes. Using this nonparametric method, the authors find that under weak assumptions, the NSLP reduces the rate of poor health, food insecurity, and obesity. Specifically, participation in the NSLP by income-eligible students reduces the rate of obesity by 17 percent (3.2 percentage points), contradicting Schanzenbach and Millimet et al.'s results.

This brief review of the previous literature illustrates the complexity in determining a causal effect of the NSLP on childhood obesity. It appears that the school lunches provide a

larger lunch with more nutrients than lunches from home (Gleason & Sutor, 2003; Campbell et al., 2011). For low-income students coming from households unable to provide breakfast or dinner, participating in the NSLP may reduce malnutrition and be beneficial to overall health. For other students, the NSLP may contribute to obesity but only by a small amount. The remainder of this paper is organized as follows. The next section describes the data and provides summary statistics of variables used in the analyses. The fourth section presents four approaches to estimating the effect of the NSLP on childhood obesity. Methods and results are reported for 1) ordinary least squares regression (OLS), 2) recursive bivariate probit model, 3) nonparametric bounds estimation, and 4) regression discontinuity design. The final section offers concluding remarks.

III. Data

Data are obtained from the National Health and Nutrition Examination Surveys (NHANES). NHANES includes interviews and medical examinations of a nationally representative sample of about 5,000 Americans annually; about half are children. Clusters of households within predetermined counties are selected and one or more persons from each household are chosen to participate in the survey. Sampling weights are used to find accurate estimates and standard errors. To increase the sample size and account for any unobserved changes over time, we use a pooled cross-sectional sample of children who attended elementary, middle, and high school between 2001 and 2008 and include survey year as a dummy variable.

All data used in the analysis come from the household interviews, with the exception of body measurements obtained in the medical examinations. These measurements are used to calculate three measurements of obesity used as outcomes in the analyses: body mass index (BMI), percent body fat, and waist to height ratio. The head of household, defined as a

household member 18 years or older that rents or owns the residence, provides all information pertaining to the household and may assist minors in their individual interview (NHANES 2009). Like all self-reported data, NHANES may have reliability issues. For example, the respondent may be unfamiliar with the specific household management, such as household income. Furthermore, under-reporting of participation in government programs such as the NSLP may occur, biasing estimates (Gunderson et al, 2012).

Outcomes

Previous research has usually measured obesity through an individual's BMI. A child i is defined as obese if his or her Body Mass Index ($BMI = \text{kg/m}^2$) is greater than the age and gender-specific threshold, $BMI_{i,95\%}$. This threshold is calculated by the Center for Disease Control's (CDC) as greater than the 95th percentile for weight based on growth charts. BMI does not allow distinctions between fat and muscle, possibly creating measurement error of very muscular individuals as obese. However, it is the most prevalent measure of overweight because it is easy to calculate using standard equipment. The indicator variable BMI_i measures whether the i^{th} child is obese ($BMI_i = 1$) or not ($BMI_i = 0$).

In addition, we include two other indicators of obesity used in the nutrition science literature: body fat and waist to height ratio. Percent body fat is measured using the Slaughter et al. equation of body density (Slaughter, et al. 1988). This equation uses triceps and subscapular skinfold measurements to calculate percent body fat and is considered to be a valid measure for children (Reilly et al., 1995). Body fat measurements require specialized equipment to measure and therefore are less often used than BMI. However, this more refined measurement does distinguish between muscle and fat. A child is considered to have a high body fat if the total

percent of body fat is greater than 30 percent. The indicator variable $Body\ Fat_i$ measures whether the i^{th} child has high percent body fat ($Body\ Fat_i=1$) or not ($Body\ Fat_i=0$).

The third outcome used in the analysis is waist to height ratio. This measure of central adiposity (fat distribution) is easy to calculate and may be a more sensitive predictor of cardiovascular disease and diabetes than BMI (Browning et al., 2010). A person with a waist to height ratio greater than 0.5 is considered obese and at risk of cardiovascular disease (Browning et al. 2010), thus the indicator variable $WtH\ Ratio_i$ measures whether child i has a large (greater than 0.5) waist to height ratio ($WtH\ Ratio_i=1$) or not ($WtH\ Ratio_i=0$).

Control Variables

A child's body composition depends on age, gender, race, calories consumed and calories burned, and genetics. For example, females are more likely to store energy as fat instead of muscle and children with obese parents may be genetically predisposed to obesity. NHANES includes myriad health, socio-economic, and nutritional outcomes, but information on parental height, weight, or health is unfortunately not provided and thus the genetic component of body composition remains unobserved. Instead, birth weight is included to control for genetic and biological factors. An appropriate measure of calories burned (exercise) is not available across all years, so two measures of inactivity are included in the analysis: average daily hours watching television and using the computer. We expect that the more time spent at either activity, the fewer hours spent engaged in physical activity and thus the more likely a child is obese. Two-day dietary recall information is provided for only a very limited number of individuals, so a measure of calorie input is not included in the analyses.

To control for characteristics across households, education, income, and marital status of the household reference are included as covariates. Household education is measured by the

education attainment of the female head of household. Female education level is used instead of male because we assume that in most households the female adult makes most decisions about food, including whether the child brings a lunch from home instead of eating a school lunch. Household income is measured as the income to poverty ratio (PIR); a PIR of 2 means a household's income is 200% of the poverty line. Measuring income relative to poverty is helpful in some of the analyses because it identifies income eligible students ($PIR < 1.85$). Additionally, because the poverty line changes annually, PIR does not need to be adjusted by the consumer price index (CPI). Table 1 provides details of all variables used in the analysis.

Not all variables selected are ideal. Household education level is measured by the education level of the female head of household and does not include a measure of the male head of household's (if present) level of education. Therefore, if the female head of household has only graduated high school but her spouse attended college, the household is reported to have the same level of education as a household with two high school graduates. This may bias the estimates positively or negatively.

Summary Statistics

The sample includes 6,410 students in elementary, middle, or high school who participated in the NHANES interview and medical examination. Only students attending schools that serve school lunch are included. Descriptive statistics of key variables can be found in table 2. The average age within the sample is 10.6 years old and 47 percent of the sample attends elementary school. The average PIR for all students is 252 percent of the poverty level. For a family of four in 2008, this is equivalent to approximately \$53,000. 14.8 percent of all students sampled are obese, 16.8 percent have high percent body fat, and 29.2 percent of all students sampled have large waist to height ratios. This result suggests that *Body Fat* is more closely correlated with *BMI* than *WtH*

Ratio; in fact, 17.2 percent of students identified as not obese have large waist to height ratio while only 7.6 percent of students classified as not obese have high body fat. 40.3 percent of all students participate in the school lunch program 5 days per week.

Similarly to previous research, we find significant differences with NSLP participants and non-participants as well as between obese and non-obese children (Dunifon and Kowaleski-Jones, 2001; Ogden & Carroll, 2010). Both obese students and NSLP participants are more likely to come from lower-income households: on average non-participants have a household income of 313 percent of the poverty line compared to 216 percent for NSLP participants. The difference between household income among obese and non-obese students is smaller but still significant. On average, obese students in the sample are 0.23 pounds heavier at birth than non-obese students, suggesting the possibility of an unobserved genetic component of obesity. The majority of students sampled are non-Hispanic white. Although Mexican Americans make up only 12.30 percent of the sample, 53.9 percent of all NSLP participants are Mexican American, 18.7 percent are white, and 14.9 percent are black.

The summary statistics for household education seem unusual. 22.9 percent of the students sampled come from households where the female head of household is a college graduate. Interestingly, 25.7 percent of NSLP participants sampled come from households where the female is a college graduate while only 10.9 percent of non-participants is come from households where the female is a college graduate. It may be possible that as the female's level of education increases, her time is more valuable and she chooses not to prepare a lunch for the child.

IV. Measuring the Effect of NSLP

This section presents four approaches to estimating the effect of National School Lunch Program

participation on childhood obesity measured through BMI, percent body fat, and waist to height ratio. We begin with OLS regression. Second, results of the recursive bivariate probit model similar to Millimet et al. (2010) are presented. The third approach recreates the nonparametric bounds approach used by Gunderson et al. (2012) but includes two new outcomes. Lastly, the fourth approach borrows from Schanzenbach (2009) by using RD design to estimate the local average treatment effect of participation. For the sake of brevity, we focus on the interpretation of the treatment effect and do not discuss the effects of the other covariates. However, all results are presented in tables 3 through 7.

Approach One: Ordinary Least Squares Regression

The first approach in determining the effect of participating in the NSLP on childhood obesity is the OLS regression. It is well known that a linear regression model will not provide consistent estimates when modeling binary outcomes because it ignores the discreteness of the variable; this approach serves primarily as a baseline comparison for the subsequent methods. The regression models are defined as:

$$(1.1) \quad BMI_i = \alpha_{BMI} + \mathbf{x}'_i \beta_{BMI} + \mathbf{h}'_i \delta_{BMI} + \mathbf{g}'_i \gamma_{BMI} + NSLP_i \tau_{BMI} + \varepsilon_{i,BMI}$$

$$(1.2) \quad Body\ Fat_i = \alpha_{BF} + \mathbf{x}'_i \beta_{BF} + \mathbf{h}'_i \delta_{BF} + \mathbf{g}'_i \gamma_{BF} + NSLP_i \tau_{BF} + \varepsilon_{i,BF}$$

$$(1.3) \quad WtH\ Ratio_i = \alpha_{WtH} + \mathbf{x}'_i \beta_{WtH} + \mathbf{h}'_i \delta_{WtH} + \mathbf{g}'_i \gamma_{WtH} + NSLP_i \tau_{WtH} + \varepsilon_{i,WtH}$$

Let \mathbf{x}'_i be a vector of individual covariates including age, gender, and race. Let \mathbf{h}'_i be a vector of health indicators that contribute to increased measures of obesity (birth weight, daily television use, and daily computer use) and \mathbf{g}'_i be a vector of household demographics including education, income, marital status, and survey year. The indicator variable $NSLP_i$ measures whether student i participates in the school lunch program ($NSLP_i = 1$) or not ($NSLP_i = 0$). Let BMI_i , $Body\ Fat_i$, and $WtH\ Ratio_i$ be the discrete obesity measurements of student i , as previously defined. Let ε_i

be the error term.

Results of the OLS regression are similar across all three models (table 3). The overall fit of the models is very low with R^2 between 3.5 percent and 6.7 percent. The estimates in table 3 are not weighted to account for survey design, however we find no significant difference between weighted and non-weighted results. We find statistically insignificant and small coefficients *NSLP* ranging from 0.008 to -0.007. This suggests that participating in the NSLP increases your probability of being obese (measured by *BMI*) by less than 1 percentage point. Contrarily, participating in the NSLP decreases your probability of having high percentage of body fat by 0.7 percentage points. These estimates are similar in magnitude to results in Schanzenbach (2009). Similar results are found when health and household characteristics are not controlled (i.e., when \mathbf{h}'_i and \mathbf{g}'_i are not included in equations 1.1-1.3).

This model assumes that participation in the NSLP is exogenous. However, it is likely that many of the observable covariates and unobservable characteristics impacting the decision to participate may also impact the probability of being obese. The next approach tries to account for potential endogeneity of *NSLP* due to nonrandom selection.

Approach Two: Recursive Bivariate Probit Model

The recursive bivariate probit model allows for the endogeneity of NSLP participation but requires strong distributional assumptions of the error term. Millimet et al. (2010) use this model “to assess the impact of positive selection” into the School Breakfast Program and note that while the model is identified without exclusion restrictions, the bivariate probit model will not provide consistent estimates without a valid instrument. We are currently attempting to determine a valid instrument and present our preliminary results here. Even without a valid instrument for participation, the bivariate probit model should be an improvement from the OLS

regression. We use the same outcome variables and covariates as described above in this two-equation model.

(2.1)

$$BMI_i^* = \mathbf{x}'_i \boldsymbol{\beta}_{BMI} + \mathbf{h}'_i \boldsymbol{\delta}_{BMI} + \mathbf{g}'_i \boldsymbol{\gamma}_{BMI} + NSLP_i \tau_{BMI} + \varepsilon_{i1,BMI}, \quad BMI_i = 1 \text{ if } BMI_i^* > BMI_{i,95\%}, \text{ else } 0$$

$$NSLP_i^* = \mathbf{x}'_i \boldsymbol{\lambda}_{BMI} + \mathbf{g}'_i \boldsymbol{\gamma}_{BMI} + \varepsilon_{i2,BMI}, \quad NSLP_i = 1 \text{ if } NSLP_i^* > 0, \text{ else } 0$$

(2.2)

$$Body\ Fat_i^* = \mathbf{x}'_i \boldsymbol{\beta}_{BF} + \mathbf{h}'_i \boldsymbol{\delta}_{BF} + \mathbf{g}'_i \boldsymbol{\gamma}_{BF} + NSLP_i \tau_{BF} + \varepsilon_{i1,BF}, \quad Body\ Fat_i = 1 \text{ if } Body\ Fat_i^* > .30, \text{ else } 0$$

$$NSLP_i^* = \mathbf{x}'_i \boldsymbol{\lambda}_{BF} + \mathbf{g}'_i \boldsymbol{\gamma}_{BF} + \varepsilon_{i2,BF}, \quad NSLP_i = 1 \text{ if } NSLP_i^* > 0, \text{ else } 0$$

(2.3)

$$WtH\ Ratio_i^* = \mathbf{x}'_i \boldsymbol{\beta}_{WH} + \mathbf{h}'_i \boldsymbol{\delta}_{WH} + \mathbf{g}'_i \boldsymbol{\gamma}_{WH} + NSLP_i \tau_{WH} + \varepsilon_{i1,WH}, \quad WtH\ Ratio_i = 1 \text{ if } WtH\ Ratio_i^* > 0.5, \text{ else } 0$$

$$NSLP_i^* = \mathbf{x}'_i \boldsymbol{\lambda}_{WH} + \mathbf{g}'_i \boldsymbol{\gamma}_{WH} + \varepsilon_{i2,WH}, \quad NSLP_i = 1 \text{ if } NSLP_i^* > 0, \text{ else } 0$$

Because $NSLP_i$ is endogenous to the three outcomes, BMI_i , $Body\ Fat_i$, and $WtH\ Ratio_i$, $NSLP_i$ is simultaneously determined in this model. The first equation in each model includes vectors of individual, health, and household explanatory variables defined in the previous section as \mathbf{x}'_i , \mathbf{h}'_i and \mathbf{g}'_i , respectively. These variables are selected to control for possible household and environmental factors. The second equation in each model does not include covariates controlling for health.

To find consistent estimators of the model, the log likelihood function for each bivariate probit model is maximized:

$$(2.4) \quad LLF = \sum_{i=1}^n \ln \Phi_2 \left(q_{i1} \left(\mathbf{x}'_i \boldsymbol{\beta}_{Y_1} + \mathbf{h}'_i \boldsymbol{\delta}_{Y_1} + \mathbf{g}'_i \boldsymbol{\gamma}_{Y_1} + NSLP_i \tau_{Y_1} \right), q_{i2} \left(\mathbf{x}'_i \boldsymbol{\lambda}_{Y_1} + \mathbf{g}'_i \boldsymbol{\gamma}_{Y_1} \right), q_{i1} q_{i2} \rho_{Y_1} \right)$$

where

$$\Phi_2(\bullet) = Pr[Y_1 = y_{i1}, NSLP = y_{i2} | \mathbf{x}, \mathbf{h}, \mathbf{g}, NSLP] = \int_{-\infty}^{\mathbf{x}'_i \boldsymbol{\lambda} + \mathbf{g}'_i \boldsymbol{\gamma}} \int_{-\infty}^{\mathbf{x}'_i \boldsymbol{\beta} + \mathbf{h}'_i \boldsymbol{\delta} + \mathbf{g}'_i \boldsymbol{\gamma} + \tau NSLP} \phi_2(z_1, z_2, \rho_{Y_1}) dz_1 dz_2$$

$$q_{ij} = \begin{cases} 1 & \text{if } y_{ij} = 1 \\ -1 & \text{if } y_{ij} = 0 \end{cases} \quad \forall j = 1, 2$$

The log-likelihood function, LLF , is the summation of the four possible combinations of Y_1 and $NSLP$. Let Y_1 be the chosen measure of obesity (either *BMI*, *Body Fat*, or *WtH Ratio*). The standard normal bivariate distribution, $\Phi_2(\cdot)$, requires both error terms ε_{1,Y_1} and ε_{2,Y_1} have a mean of zero and variance of one. The covariance (or disturbance term) between ε_{1,Y_1} and ε_{2,Y_1} is ρ_{Y_1} . If the $\rho_{Y_1} = 0$, the model reduces to a recursive probit model where $NSLP_i$ is still determined simultaneously. If $\rho_{Y_1} \neq 0$, the error terms ε_{1,Y_1} and ε_{2,Y_1} are positively or negatively correlated, depending on the sign of ρ_{Y_1} . This may indicate selection bias on unobservables as well (Altonji et al., 2005; Millimet et al., 2010). It is important to note that a non-zero disturbance term may be due to true correlation between childhood obesity and NSLP participation as well as specification error within the model.

Table 4 provides the estimated coefficients for the recursive bivariate probit model. Again, results across the three models are similar. The coefficient τ_{Y_1} ranges from is 0.705 to 0.805 and is statistically significant in the *BMI* and *WtH Ratio* models, suggesting that participation in the school lunch program increases the likelihood of being obese. The coefficient τ_{NSLP} is not significant when *Body Fat* is the outcome. The disturbance term is estimated to be negative and statistically different than zero. This is a surprising and a somewhat counterintuitive result: after accounting for individual and household characteristics and the effect of NSLP participation on obesity rates, there is a significant negative correlation between unobservables in the two equations. Recall that this term is due to either true correlation or specification error in the model. If the model is specified appropriately, this result may indicate negative selection into the school lunch program.

The marginal effects of NSLP participation on the three health outcomes are also included in table 4. All three marginal effects are positive and statistically significant. The probability of being obese ($Y_i=BMI$) is 11.7 percentage points higher for students participating in the school lunch program. The probability of having a high percentage of body fat increases 9.0 percentage points for participants and the probability of having a large waist to height ratio increases 18.3 percentage points for students participating in the NSLP. This estimate is significant and supports studies finding increased fat intake of NSLP participants (e.g. Gleason & Sutor, 2003; Campbell et al., 2011) and those finding positive relationships between participation and obesity (e.g. Millimet et al., 2010; Schanzenbach, 2009). However, without a valid instrument, a causal effect of participation in the NSLP on childhood obesity cannot be determined with the bivariate probit model. The next approach uses nonparametric methods to partially identify the average treatment effect without restrictive parametric assumptions.

Approach Three: Nonparametric Bounds

The previous models have dealt with endogenous treatment selection by imposing strict parametric assumptions (recursive bivariate probit model) or ignoring them completely (OLS regression). In contrast, the third approach uses nonparametric bounds to partially identify the ATE. We observe $\mathbf{x} = (w, z)$, a set of covariates within $\mathbf{X} = \mathbf{W} \times \mathbf{Z}$ defining each subpopulation. Let y_1 be a student's potential health outcome if participating in NSLP and let y_0 be a student's potential health outcome if not participating in NSLP. For this analysis, y_i includes *BMI*, *Body Fat*, and *WtH Ratio*. The average treatment effect is

$$(3.1) \quad ATE = E[y_1|\mathbf{x}] - E[y_0|\mathbf{x}]$$

where

$$\begin{aligned}
E[y_1|\mathbf{x}] &= pE[y_1|\mathbf{x}, NSLP = 1] + (1-p)E[y_1|\mathbf{x}, NSLP = 0] \\
E[y_0|\mathbf{x}] &= pE[y_0|\mathbf{x}, NSLP = 1] + (1-p)E[y_0|\mathbf{x}, NSLP = 0] \\
p &= \Pr(NSLP = 1|\mathbf{x}) \\
E[y_t] &\in [0,1]
\end{aligned}$$

For each student, we observe either y_1 or y_0 , a binary outcome, but we do not observe the counterfactual where $E[y_t|\mathbf{x}, NSLP \neq t]$. We know, however, that the expectation must lie between 0 and 1. Unless participation in the NSLP is random, a point estimate of ATE will be biased due to potential selection on unobservables. Without including any further assumptions, Manski (1990) developed “worst-case” bounds by replacing the unobserved expectations with the bounded values of y_t . For each value of \mathbf{x} , let ATE_{WC} be defined as:

$$(3.2) \quad ATE_{WC} \in \left[pE[y_1|\mathbf{x}, NSLP = 1] - p - (1-p)E[y_0|\mathbf{x}, NSLP = 0], \right. \\
\left. pE[y_1|\mathbf{x}, NSLP = 1] + (1-p) - (1-p)E[y_0|\mathbf{x}, NSLP = 0] \right]$$

The worst-case bounds are not very informative. By definition, they must cover zero and have a width of one in the case of binary outcomes. The ATE_{WC} for $y_t = BMI$, $y_t = Body Fat$, and $y_t = WiH Ratio$ are shown in table 5. The sample is divided into 20 groups defined by the PIR and an appropriately weighted ATE_{WC} calculated for each group.³ Covariates in \mathbf{x} limit the sample to students between the age of 6 and 17 attending school that offers NSLP; unlike Gunderson et al., we include income-eligible and ineligible students. In finite samples, bounds other than ATE_{WC} are biased. However, with more than 400 observations in each group, the bias should be negligible (Kreider et al., 2011). At worst, participation in the NSLP increases the obesity rate by 42.6 percentage points. At best, participation decreases the obesity rate by 57.4 percentage points. Similar results are found for *Body Fat* (-0.595, 0.405) and *WiH Ratio* (-0.539, 0.461).

³ Because some \mathbf{x} are empty sets, the sample must be divided into groups. Estimates are similar when using 10 groups.

Inclusion of additional assumptions allows these bounds to be tightened to produce a more informative result without depending on strong distributional assumptions (Manski, 1990; Manski & Pepper, 2000). A common assumption (and an underlying assumption for valid instrumental variables) is mean-independence: the mean outcome for each treatment is equal across all subpopulations. If covariate z is an instrumental variable, then the worst-case bounds for each \mathbf{x} can be tightened to:

$$(3.3) \quad ATE_{IV} \in \left[\sup_z \left(pE[y_1|\mathbf{x}, NSLP = 1] \right) - \inf_z \left(p + (1-p)E[y_0|\mathbf{x}, NSLP = 0] \right), \right. \\ \left. \inf_z \left(pE[y_1|\mathbf{x}, NSLP = 1] + (1-p) \right) - \sup_z \left((1-p)E[y_0|\mathbf{x}, NSLP = 0] \right) \right]$$

ATE_{IV} are included in table 5 using household PIR as an instrument for participation in NSLP. The ATE_{IV} on *Body Fat* states that assuming students from households with varying income have the same mean health outcome, participation in the NSLP will at worst increase the probability of having high percent body fat by 10.7 percentage points and at best decrease the probability of having high percent body fat by 31.0 percentage points. However, it is much more likely that PIR is a monotone instrumental variable (MIV). That is, we expect that the probability of negative health outcomes *Body Fat*, *BMI*, and *WtH Ratio* weakly decrease with PIR, as in Gunderson et al. (2012). Formally, the negative MIV assumption states that for each treatment t , $E[y_t|w, z = z_1] \geq E[y_t|w, z = z_2]$, where z is an ordered set and $z_1 \leq z \leq z_2$. The average treatment effect using the MIV assumption produces bounds that are smaller than worst-case bounds but larger than IV bounds. Let ATE_{MIV} be

$$(3.4) \quad ATE_{MIV} \in \left[\sup_{z_1 \leq z} \left(pE[y_1|x, z = z_1, NSLP = 1] \right) - \inf_{z_2 \geq z} \left(p + (1-p)E[y_0|x, z = z_2, NSLP = 0] \right), \right. \\ \left. \inf_{z_2 \geq z} \left(pE[y_1|x, z = z_2, NSLP = 1] + (1-p) \right) - \sup_{z_1 \leq z} \left((1-p)E[y_0|x, z = z_1, NSLP = 0] \right) \right]$$

ATE_{MIV} bounds are also uninformative. The ATE_{MIV} on *WtH Ratio* states that assuming students from households with lower income have weakly higher *negative* health outcomes, participation in the NSLP will at worst increase the probability of having a large waist to height ratio by 22.8 percentage points and at best decrease the probability of having a large waist to height ratio by 51.7 percentage points. While the MIV assumption may seem “innocuous” (Gunderson et al., 2012), our sample data suggest that even this assumption is incorrect. Figure 1 graphs each expected outcome by PIR. The relationship does not appear monotone (negative or positive) across any values of PIR. Even if analysis is restricted to income-eligible students, the expected values of *BMI*, *Body Fat*, and *WtH Ratio* appear to fluctuate between PIR values of 0 and 1.85.

A more common assumption in the literature is selection on unobservables. Models that assume exogenous selection (e.g., OLS regression) will calculate biased treatment effect estimates if positive or negative selection exists. Although the bivariate probit model estimated above found possible negative selection through the covariance term ρ , it is generally assumed that unobserved characteristics associated with obesity are positively related to participation in the NSLP (Currie, 2003). We now formalize the assumption of positive selection, or monotone treatment selection (MTS) assumption (Manski & Pepper, 2000) within the ATE framework. In terms of this analysis, the MTS assumption states that a student participating in the NSLP is likely to have no better *negative* health outcome on average than non-participants. Thus the bounds of the expected outcomes are now:

$$0 \leq E[y_1 | \mathbf{x}, NSLP = 0] \leq E[y_1 | \mathbf{x}, NSLP = 1] \leq 1$$

$$1 \geq E[y_0 | \mathbf{x}, NSLP = 1] \geq E[y_0 | \mathbf{x}, NSLP = 0] \geq 0$$

The MTS assumption does not change the lower bound of ATE_{WC} but does decrease the upper bound. This result is intuitive: if positive selection exists, we expect estimates assuming

exogenous selection to be biased upward. Thus the ATE_{MTS} has the same lower bound of equation 3.2 and the upper bound is now

$$(3.5) \quad ATE_{MTS} \leq pE[y_1|\mathbf{x}, NSLP = 1] + (1-p)E[y_1|\mathbf{x}, NSLP = 1] \\ - pE[y_0|\mathbf{x}, NSLP = 0] - (1-p)E[y_0|\mathbf{x}, NSLP = 0].$$

The estimates of ATE_{MTS} for each outcome are in table 5. Including the MTS assumption tightens the lower bounds for all outcomes and finds negative upper bounds for *Body Fat* and *WaH Ratio*. Assuming positive selection, at worst participating in the NSLP 1) increases the probability of being obese by less than 1 percentage point, 2) decreases the probability of having high percent body fat by 3.7 percentage points, and 3) decreases the probability of having a large waist to height ratio by 1.6 percentage points. Unlike the MIV assumption, the authors know of no test or figure used to evaluate the validity of the MTS assumption. However, the assumption of positive MTS seems much more likely than exogenous treatment selection or negative MTS.

Lastly, although we question the validity of the MIV assumption, we present the combined MIV and MTS assumption because it may be applicable in other research scenarios.

Let $ATE_{MIV+MTS}$ be

$$(3.6) \quad ATE_{MIV+MTS} \in \left[\sup_{z_1 \leq z} (LB_1(z_1)) - \inf_{z_2 \geq z} (UB_0(z_2)), \inf_{z_2 \geq z} (UB_1(z_2)) - \sup_{z_1 \leq z} (LB_0(z_1)) \right]$$

where

$$LB_1(z_1) = pE[y_1|x, z = z_1, NSLP = 1] \\ UB_1(z_2) = pE[y_1|\mathbf{x}, NSLP = 1] + (1-p)E[y_1|\mathbf{x}, NSLP = 1] \\ LB_0(z_1) = pE[y_0|\mathbf{x}, NSLP = 0] - (1-p)E[y_0|\mathbf{x}, NSLP = 0] \\ UB_0(z_2) = p + (1-p)E[y_0|x, z = z_2, NSLP = 0]$$

Again, the positive MTS assumption only changes the upper bounds of each $ATE_{MIV+MTS}$. The lower bounds are identical to the ATE_{MIV} lower bounds. Assuming students from households with lower income have weakly higher *negative* health outcomes in addition to assuming positive selection on unobservables, at worst participating in the NSLP 1) decreases the probability of being obese by 5.4 percentage points, 2) decreases the probability of having high percent body fat by 14.7 percentage points, and 3) decreases the probability of having a large waist to height ratio by 9.8 percentage points. When including income-eligible and ineligible students, the average treatment effect for *BMI* is 2.2 percentage points higher than estimated by Gunderson et. al (2012).

The nonparametric bounds approach suggests that under weak assumptions, the average treatment effect of participation in the NSLP on indicators of high percent body fat, obesity, and large waist to height ratio is at worst negative. This result contradicts the results from approach 1 and 2 in this paper as well as results in the previous literature (including Millimet et al. (2010) and Schanzenbach (2009)). The final approach to treatment evaluation is regression discontinuity design.

Approach Four: Regression Discontinuity

Regression discontinuity takes advantage of the large disparity between the price of a school lunch for income-eligible students and income-ineligible students that increases the probability of participation for income-eligible students. By law, the reduced price lunch can cost the student no more than \$0.40 while a “full price” meal on average costs \$1.80⁴ (School Nutrition Association, 2007). Because income-eligible students are not required to participate and income-

⁴ The cost of a “full price” meal is set locally and thus varies from school to school. As of 2012, each “full price” lunch served is federally subsidized \$0.26, much lower rate than the subsidy rate for free and reduced price lunches. State and local governments can choose to subsidize full price meals even more. For example, “full price” meals in New York City are currently set at \$1.50.

ineligible students may choose to participate and pay full price, we use a fuzzy regression discontinuity design (FRD) such that

$$\lim_{PIR \downarrow PIR^0} \Pr(NSLP_i = 1 | PIR_i = PIR^0) \neq \lim_{PIR \uparrow PIR^0} \Pr(NSLP_i = 1 | PIR_i = PIR^0)$$

where $PIR^0=1.85$ is the threshold. In our sample, the probability of participating in NSLP decreases from 59 percent to 73.3 percent around the threshold, PIR^0 . Let the relationship between the three outcomes and participation in the NSLP be

$$(4.1) \quad BMI_i = \alpha_{BMI} + NSLP_i \tau_{BMI} + f(PIR_i) + v_{i,BMI}$$

$$(4.2) \quad Body\ Fat_i = \alpha_{BF} + NSLP_i \tau_{BF} + f(PIR_i) + v_{i,BF}$$

$$(4.3) \quad WtH\ Ratio_i = \alpha_{WtH} + NSLP_i \tau_{WtH} + f(PIR_i) + v_{i,WtH}$$

where $NSLP_i$ and PIR_i are defined as before, τ_{y_i} is the local average causal effect (LATE) of participation, and v_{i,y_i} is a vector of covariates influencing the outcome variable (age, gender, race, and birth weight). The estimand of τ_{y_i} is the ratio of the magnitude of the discontinuity in the probability of each outcome to the magnitude of the discontinuity in the probability of participating in the school lunch program⁵ (Imbens & Lemieux, 2007):

$$(4.4) \quad \tau_{y_i} = \frac{\lim_{PIR \downarrow PIR^0} E[y_i | PIR_i = PIR^0] - \lim_{PIR \uparrow PIR^0} E[y_i | PIR_i = PIR^0]}{\lim_{PIR \downarrow PIR^0} E[NSLP_i | PIR_i = PIR^0] - \lim_{PIR \uparrow PIR^0} E[NSLP_i | PIR_i = PIR^0]}$$

where y_i is student i 's obesity outcome (BMI , $Body\ Fat$, or $WtH\ Ratio$). The LATE estimand τ is determined by using local linear regressions to estimate the outcome variable on either side of the threshold $PIR=1.85$ (the numerator of τ_{y_i}) and then using local linear regression again to estimate the treatment effect on either side of the threshold (the denominator of τ_{y_i}).

⁵ The sharp regression discontinuity design is a special case of FSD where the discontinuity in regression of the treatment indicator is 1.

Results are presented in table 6 and figures 2 through 4. Optimal bandwidth is defined by the IK bandwidth (Imbens & Kalyanaraman, 2009). Standard errors are estimated using the delta method. Figure 2 graphs the smoothed probability of being obese over all values of PIR. The vertical line represents the threshold value of $PIR=1.85$, with income-eligible students to the left of the cutoff and income-ineligible students to the right of the cutoff. A discontinuity is present at the cutoff, but it appears small. Unlike Schanzenbach (2009), we find that students just above the threshold are more likely to be obese. That is, participation in the school lunch program decreases the probability of being obese by 78 percentage points. Although the result is insignificant and the magnitude highly improbable, the negative sign is congruent with the nonparametric bounds estimated above. Figures 3 and 4 show similar results for indicators of high body fat and large waist to height ratio. Participation in the NSLP reduces the probability of high percent body fat by 132 percentage points and reduces the probability of large waist to height ratio by 198 percentage points. Again, these estimates seem very unrealistic and are not significantly different than zero.

The authors calculate standard robustness checks on the validity of the FRD design. To make sure the discontinuity is not present at other thresholds, τ_{y_i} is estimated at $PIR^0=2$ (included in table 6), $PIR^0=2.5$, and $PIR^0=1$. The coefficients at each false threshold are not significant. Another specification test is calculated by running regressions on baseline covariates *Birth Weight* and *Black, non-Hispanic* that should not affect participation in the NSLP and thus we expect continuity in each of these covariates at the threshold. As expected, neither of these coefficients is significant. The coefficient estimates do not depend on bandwidth: decreasing the bandwidth to half the size of the IK optimal bandwidth and increasing it to twice as large produces similar results. Lastly, local linear regressions estimated with and without

covariates also produce similar results. If the inclusion of covariates changes the significance or sign of the estimated LATE, this may indicate misspecification of the FRD or a potential discontinuity in one or more covariates. While our specification tests indicate valid FRD design, the estimated treatment effects for BMI, Body Fat, and WtH Ratio are all insignificant. It may be the case that the small discontinuity is caused by non-linearity of the conditional mean function. As shown in figure 1, the expected value of each of the outcomes is not monotonic across all values of PIR. A test of monotonicity in the conditional mean outcomes for students just above and just below the threshold should be calculated.

V. Summary and Conclusions

The National School Lunch Program is one of the largest food-assistance programs in the United States, providing lunch for over 31 million students. Recent research suggests that the NSLP is no longer providing nutritious meals and at least one-third of schools do not meet compliance set by the *Dietary Guidelines of America* (Crepinski et al., 2009). With childhood obesity close to 17 percent for two- to nineteen-year olds, it is imperative to understand how participation in the NSLP may be impacting childhood obesity.

Previous studies have shown that participation in the NSLP contributes to childhood obesity, most likely through the high fat and calorie content of the school lunch as well as due to selection on unobservables. However, under weaker assumptions, the positive effects of participation on negative health outcomes disappear. This paper reviews the current literature on the causal impacts of the NSLP on obesity and other nutritional outcomes and then offers four approaches to estimation. We add to the economics literature two additional measures of obesity: percent body fat and waist to height ratio. However, the findings are inconclusive. Using OLS regression, the estimated effect of participation on obesity is less than 1 percentage

point; using a recursive bivariate probit model, participation in the NSLP increases the probability of being obese by 12 percentage points. When strong normality distributions are removed, these estimates reverse sign: under MIV and MTS assumptions, participation in the NSLP at worst decreases the probability of being obese 5 percentage points; estimation of a local average treatment effect around the income-eligibility threshold of 185 percent of the poverty line indicates that participation in the NSLP decreases the probability of being obese by 78 percentage points.

The causal relationship between participation in the NSLP and rates of childhood obesity is still unclear, partly due to concerns about the validity of each model. The simplistic OLS regression does not account for the endogeneity of participation, however the more complex bivariate probit model requires a valid instrument to correctly identify the causal effect and results may depend heavily on the strong distributional assumptions. Unfortunately, even the most “innocuous” assumption of conditional mean monotonicity is not supported by the data, thus invalidating the nonparametric MIV bounds and possibly the fuzzy regression discontinuity results. These conclusions underscore the complexity in determining a causal effect of the NSLP on childhood obesity. Future research may focus on determining the precise mechanism through which the school lunch program has an effect on obesity.

VI. References

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Table 1. Variables

Variable	
Measures of Obesity	
<i>BMI</i>	Individual Body Mass Index (BMI) is greater than age/gender specific cutoff for obese (Yes or No)
<i>Body Fat</i>	Individual percent body fat is greater than 30% for obese (Yes or No)
<i>WtH Ratio</i>	Individual waist to height ratio is greater than .50 for obese (Yes or No)
Individual Characteristics	
<i>NSLP</i>	Individual participates in National School Lunch Program (NSLP) five days per week (Yes or No)
<i>Age</i>	Individual's age (years)
<i>Gender</i>	Individual's gender (Male or Female)
<i>Race</i>	Individual's race (Non-Hispanic White, Non-Hispanic Black, Mexican American, and Other)
Health Indicators	
<i>Birth Weight</i>	Individual's weight at birth (lbs)
<i>Daily Television Use</i>	Average hours per day individual spends watching TV (Less than 1, 1, 2, 3, 4, 5, 5+ hours)
<i>Daily Computer use</i>	Average hours per day individual spends using the computer (Less than 1, 1, 2, 3, 4, 5, 5+ hours)
Household Demographics	
<i>Education</i>	Education level of female household reference (Less than high school, high school diploma or GED, some college, college graduate or above)
<i>Income/Poverty</i>	Ratio of household income to federal poverty line (e.g. 1 = household income is at poverty line)
<i>Marital Status</i>	Marital status of household reference (Married, divorced or separated, other)
<i>Survey Year</i>	Year of questionnaire and medical examination (2001-2002, 2003-2004, 2005-2006, 2007-2008)

Table 2. Descriptive Statistics

Variable	All Students	NSLP Participants	NSLP Non-Participants	Obese Students	Non-Obese Students
<i>NSLP Participant</i>	40.30% (0.016)	100.00% -	0.00% -	65.00% *** (0.024)	58.80% (0.016)
<i>NSLP Non-Participant</i>	59.70% (0.016)	0.00% -	100.00% -	35.00% *** (0.024)	41.20% (0.016)
<i>Obese</i>	14.80% (0.006)	16.10% *** (0.007)	12.90% (0.008)	100.00% *** -	0.00% -
<i>High Percent Body Fat</i>	16.80% (0.007)	16.40% *** (0.008)	17.30% (0.011)	69.40% *** (0.023)	7.60% (0.007)
<i>Large Waist to Height Ratio</i>	29.20% (0.009)	29.90% *** (0.010)	28.20% (0.014)	97.80% *** (0.005)	17.20% (0.010)
<i>Age</i>	10.577 (0.050)	10.425 *** (0.056)	10.831 (0.090)	10.689 *** (0.082)	10.551 (0.059)
<i>Birth Weight</i>	7.325 (0.025)	7.29 *** (0.034)	7.384 (0.035)	7.514 *** (0.049)	7.283 (0.026)
<i>Household Income/Poverty</i>	2.52 (0.053)	2.156 *** (0.054)	3.131 (0.060)	2.19 *** (0.065)	2.593 (0.053)
Race					
<i>White, non-Hispanic</i>	60.70% (0.029)	18.70% *** (0.023)	9.20% (0.013)	16.80% * (0.022)	14.50% (0.018)
<i>Black, non Hispanic</i>	14.80% (0.018)	14.90% *** (0.022)	8.40% (0.014)	15.10% *** (0.024)	11.80% (0.018)
<i>Mexican American</i>	12.30% (0.018)	53.90% *** (0.033)	70.80% (0.026)	56.60% *** (0.036)	61.40% (0.029)
<i>Other</i>	12.20% (0.011)	12.50% (0.013)	11.70% (0.013)	11.50% (0.014)	12.30% (0.012)
Household Education					
<i>Less than HS</i>	19.70% (0.016)	24.90% ** (0.012)	22.40% (0.016)	30.90% *** (0.021)	22.70% (0.011)
<i>HS Diploma/GED</i>	23.90% (0.011)	31.90% *** (0.016)	35.90% (0.016)	30.60% ** (0.023)	34.00% (0.015)
<i>Some College</i>	33.50% (0.013)	17.50% *** (0.014)	30.80% (0.019)	15.60% *** (0.018)	24.10% (0.014)
<i>College Graduate</i>	22.90% (0.013)	25.70% *** (0.019)	10.90% (0.014)	22.90% ** (0.021)	19.20% (0.016)
Number of Observations	6,410	4,208	2,202	1,039	5,371

Notes: Estimates are weighted appropriately for survey design and standard errors are shown in parentheses. Asterisk (*), double asterisk (**), and triple asterisk (***) indicate mean is significantly different than non-obese or non-participant population at $\alpha = 10\%$, 5% and 1% , respectively.

Table 3. OLS Regression Results

Explanatory Variable (Omitted Level)	Measure of Obesity		
	BMI	Body Fat	WtH Ratio
<i>NSLP Participant</i>	0.008 (0.012)	-0.007 (0.012)	0.003 (0.014)
Individual Characteristics			
<i>Age</i>	0.005** (0.002)	0.024*** (0.002)	0.012*** (0.002)
Gender (Omitted: Female)			
<i>Male</i>	-0.002 (0.011)	-0.101*** (0.010)	-0.063*** (0.012)
Race (Omitted: White, non-Hispanic)			
<i>Black, non-Hispanic</i>	0.021 (0.016)	-0.014 (0.015)	-0.088*** (0.018)
<i>Mexican American</i>	0.017 (0.015)	0.004 (0.015)	0.043* (0.018)
<i>Other</i>	0.023 (0.020)	0.004 (0.019)	0.003 (0.024)
Health Indicators			
<i>Birth Weight</i>	0.033*** (0.004)	0.020*** (0.004)	0.035*** (0.005)
Daily TV Use (Omitted: Less than 1)			
<i>1 Hour</i>	-0.051 (0.057)	-0.075 (0.061)	-0.004 (0.067)
<i>2 Hours</i>	-0.026 (0.056)	-0.091 (0.060)	0.021 (0.065)
<i>3 Hours</i>	0.006 (0.056)	-0.047 (0.060)	0.056 (0.065)
<i>4 Hours</i>	0.029 (0.057)	-0.038 (0.060)	0.074 (0.066)
<i>5 Hours</i>	0.049 (0.058)	-0.013 (0.062)	0.107 (0.067)
<i>5 + Hours</i>	0.08 (0.058)	0.007 (0.062)	0.141* (0.067)
Daily Computer use (Omitted: Less than 1)			
<i>1 Hour</i>	-0.011 (0.016)	-0.004 (0.015)	-0.02 (0.018)
<i>2 Hours</i>	-0.029 (0.017)	0.008 (0.016)	-0.034 (0.019)
<i>3 Hours</i>	-0.015 (0.020)	-0.012 (0.019)	-0.025 (0.023)

Explanatory Variable (Omitted Level)	Measure of Obesity		
	BMI	Body Fat	WtH Ratio
<i>4 Hours</i>	-0.029 (0.028)	0.004 (0.028)	-0.049 (0.032)
<i>5 Hours</i>	-0.03 (0.040)	-0.049 (0.036)	-0.071 (0.044)
<i>5 + Hours</i>	-0.029 (0.039)	0.035 (0.039)	-0.02 (0.045)
Household Demographics			
Poverty/Income Ratio	-0.003 (0.005)	-0.007 (0.004)	-0.014** (0.005)
Education (Omitted: Less than High School)			
<i>HS Diploma/GED</i>	-0.001 (0.016)	-0.002 (0.015)	-0.007 (0.018)
<i>Some College</i>	-0.051*** (0.015)	-0.024 (0.015)	-0.044* (0.018)
<i>College Graduate</i>	-0.082*** (0.020)	-0.044* (0.019)	-0.101*** (0.023)
Marital Status (Omitted: Married)			
<i>Divorced or Separated</i>	0.047** (0.016)	0.039* (0.016)	0.03 (0.018)
<i>Other</i>	-0.002 (0.017)	-0.001 (0.016)	-0.018 (0.019)
Survey Year (Omitted: 2001- 2002)			
<i>2003-2004</i>	0.005 (0.014)	0.009 (0.014)	0.025 (0.016)
<i>2005-2006</i>	0.033* (0.014)	0.009 (0.014)	0.035* (0.016)
<i>2007-2008</i>	0.034 (0.018)	0.007 (0.016)	0.047* (0.021)
Constant	-0.091 (0.069)	-0.102 (0.071)	-0.014 (0.079)
Number of Observations	5,546	5,203	5,493
R Squared	0.035	0.067	0.055

Notes: Asterisk (*), double asterisk (**), and triple asterisk (***) denote 10, 5, and 1 percent significance levels, respectively. Estimates shown are not weighted; there was no significant difference between weighted and non-weighted results. Similar results are found when controlling for only individual characteristics. Robust standard errors are shown in parentheses.

Table 4: Recursive Bivariate Probit Models

Explanatory Variable	Measure of Obesity					
	BMI		Body Fat		WtH Ratio	
	BMI	NSLP	Body Fat	NSLP	WtH Ratio	NSLP
<i>NSLP Participant</i>	0.705*		0.775		0.805***	
	(0.306)		(0.569)		(0.244)	
Individual Characteristics						
<i>Age</i>	0.032***	-0.058***	0.112***	-0.058***	0.050***	-0.060***
	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
<i>Male</i>	-0.045	0.188***	-0.438***	0.167***	-0.222***	0.191***
	(0.043)	(0.037)	(0.043)	(0.038)	(0.036)	(0.037)
<i>Race</i>						
<i>Black, non-Hispanic</i>	-0.004	0.343***	-0.153	0.352***	-0.348***	0.343***
	(0.071)	(0.050)	(0.094)	(0.052)	(0.055)	(0.051)
<i>Mexican American</i>	0.037	0.076	-0.012	0.073	0.073	0.085
	(0.058)	(0.051)	(0.064)	(0.055)	(0.052)	(0.052)
<i>Other</i>	0.049	0.097	-0.008	0.065	-0.026	0.099
	(0.075)	(0.068)	(0.081)	(0.071)	(0.067)	(0.068)
Health Indicators						
<i>Birth Weight</i>	0.114***		0.081***		0.093***	
	(0.016)		(0.018)		(0.014)	
<i>Daily TV Use</i>						
<i>1 Hour</i>	-0.203		-0.257		-0.015	
	(0.207)		(0.200)		(0.189)	
<i>2 Hours</i>	-0.081		-0.322		0.065	
	(0.200)		(0.196)		(0.184)	
<i>3 Hours</i>	0.037		-0.13		0.161	
	(0.198)		(0.192)		(0.183)	
<i>4 Hours</i>	0.114		-0.097		0.21	
	(0.200)		(0.194)		(0.185)	
<i>5 Hours</i>	0.18		-0.009		0.297	
	(0.204)		(0.198)		(0.188)	
<i>5 + Hours</i>	0.272		0.057		0.386*	
	(0.203)		(0.197)		(0.187)	
<i>Daily Computer Use</i>						
<i>1 Hour</i>	-0.042		-0.018		-0.056	
	(0.053)		(0.057)		(0.048)	
<i>2 Hours</i>	-0.105		0.03		-0.094	
	(0.056)		(0.060)		(0.051)	
<i>3 Hours</i>	-0.054		-0.051		-0.067	
	(0.068)		(0.074)		(0.062)	

Explanatory Variable	Measure of Obesity					
	BMI		Body Fat		WtH Ratio	
	BMI	NSLP	Body Fat	NSLP	WtH Ratio	NSLP
<i>4 Hours</i>	-0.104 (0.098)		0.015 (0.103)		-0.138 (0.088)	
<i>5 Hours</i>	-0.1 (0.135)		-0.178 (0.155)		-0.195 (0.127)	
<i>5 + Hours</i>	-0.101 (0.127)		0.128 (0.131)		-0.048 (0.119)	
Household Demographics						
Poverty/Income Ratio	0.037 (0.030)	-0.205*** (0.015)	0.033 (0.056)	-0.211*** (0.015)	0.02 (0.026)	-0.206*** (0.015)
Education						
<i>HS Diploma/GED</i>	0.045 (0.057)	-0.213*** (0.054)	0.071 (0.073)	-0.232*** (0.056)	0.037 (0.052)	-0.218*** (0.054)
<i>Some College</i>	-0.103 (0.069)	-0.301*** (0.053)	-0.001 (0.093)	-0.302*** (0.055)	-0.036 (0.058)	-0.294*** (0.053)
<i>College Graduate</i>	-0.221* (0.094)	-0.353*** (0.068)	-0.087 (0.123)	-0.339*** (0.071)	-0.189* (0.081)	-0.342*** (0.068)
Marital Status						
<i>Divorced or Separated</i>	0.180** (0.055)	-0.106* (0.053)	0.156** (0.059)	-0.082 (0.056)	0.110* (0.051)	-0.102 (0.054)
<i>Other</i>	0 (0.058)	0.002 (0.058)	0.001 (0.063)	0.003 (0.060)	-0.042 (0.054)	0.018 (0.059)
Constant	-2.551*** (0.329)	1.508*** (0.102)	-2.939*** (0.434)	1.519*** (0.105)	-2.177*** (0.292)	1.511*** (0.103)
Rho	-0.412 (0.189)		-0.481 (0.356)		-0.484** (0.151)	
<i>NSLP Marginal Effect</i>	0.117*** (0.081)		0.090*** (0.073)		0.183*** (0.116)	
Number of Observations	5,546		5,203		5,493	
Log-Likelihood	-5,796.35		-5,136.62		-6,391.58	
Chi-Square	996.2 (<0.0001)		1,137.15 (<0.0001)		1,123.80 (<0.0001)	

Notes: Asterisk (*), double asterisk (**), and triple asterisk (***) denote 10, 5, and 1 percent significance levels, respectively. Estimates shown are not weighted; there was no significant difference between weighted and non-weighted results. Robust standard errors are shown in parentheses. Survey year is included in the model but not reported. The following categorical variable levels are omitted to prevent multicollinearity: Gender (Female), Race (White, non-Hispanic), Daily Television or Computer Use (Less than 1 Hour), Female Education (Less than HS), Marital Status (Married).

Table 5. Nonparametric Bounds

<u>Assumption</u>	<u>BMI</u>	<u>Body Fat</u>	<u>WtH Ratio</u>
Worst Case	[-0.574, 0.426]	[-0.595, 0.405]	[-0.539, 0.461]
IV	[-0.268, 0.236]	[-0.310, 0.107]	[-0.195, 0.205]
MIV	[-0.548, 0.243]	[-0.572, 0.137]	[-0.517, 0.228]
MTS	[-0.574, 0.006]	[-0.595, -0.037]	[-0.539, -0.016]
MIV + MTS	[-0.548, -0.054]	[-0.572, -0.147]	[-0.517, -0.098]

Notes: Bounds found with appropriately weighted estimates. Income/Poverty Ratio is used as IV and MIV. To insure non-empty sets, the sample was divided into 20 groups. Similar results occur when the sample is only divided into 10 groups. Standard errors were not calculated.

Table 6. Regression Discontinuity Results

<u>Measure of Obesity</u>	τ (NSLP Coefficient)	Falsification: Threshold = 200% Income/Poverty	<u>Bandwidth</u>
<i>Obese</i>	-0.781 (1.196)	1.364 (3.523)	1.245
<i>Body Fat</i>	-1.321 (1.694)	-1.820 (4.062)	1.158
<i>WtH Ratio</i>	-1.980 (2.419)	0.241 (2.365)	1.229
<u>Baseline Covariates</u>			
<i>Black, non-Hispanic</i>	0.971 (1.467)	-1.439 (9.776)	1.171
<i>Birth Weight</i>	-3.189 (4.595)	-2.657 (4.384)	0.922

Each row represents a separate regression. Number of observations in each regression is 5,907. No covariates are included, although results are similar when covariates for age, race, and gender are included. Bandwidth estimated with Imbens-Kalyanaram optimal bandwidth.

Figure 1.

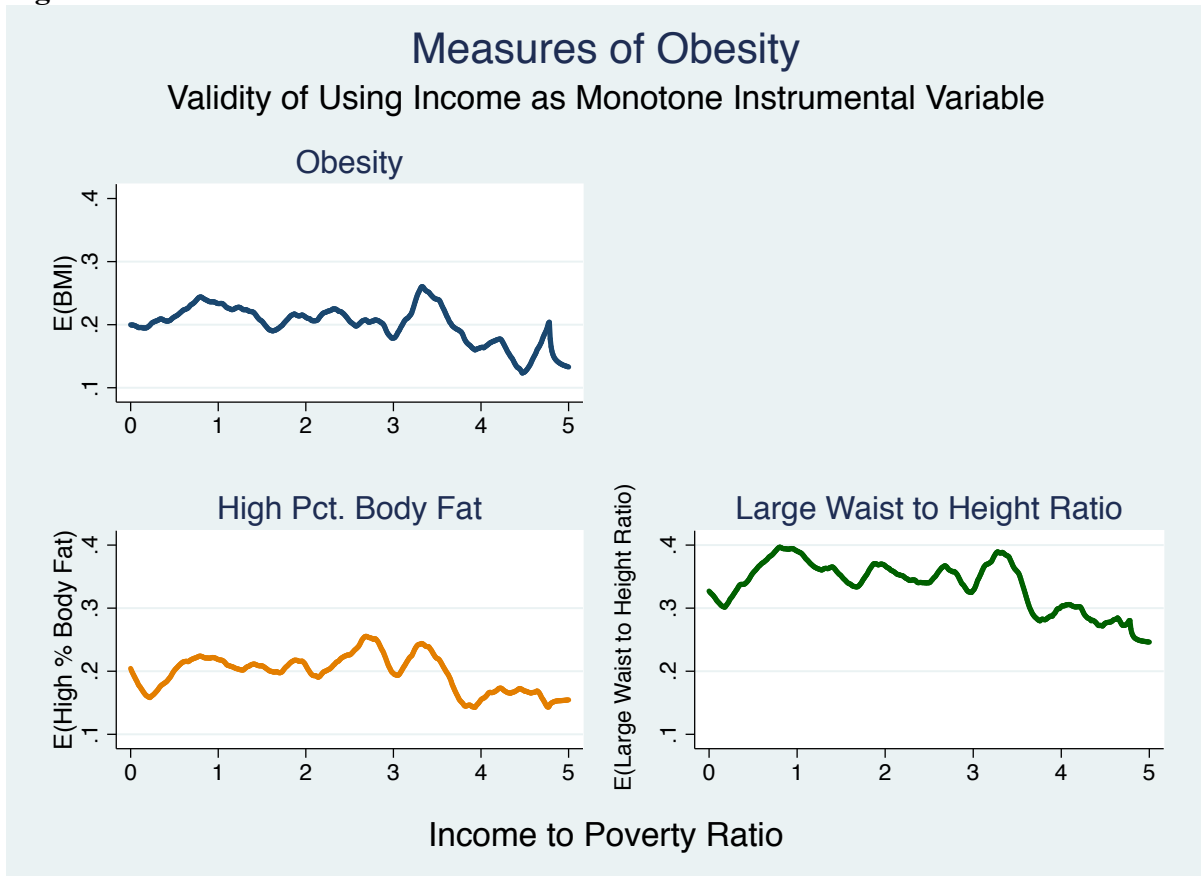


Figure 2.

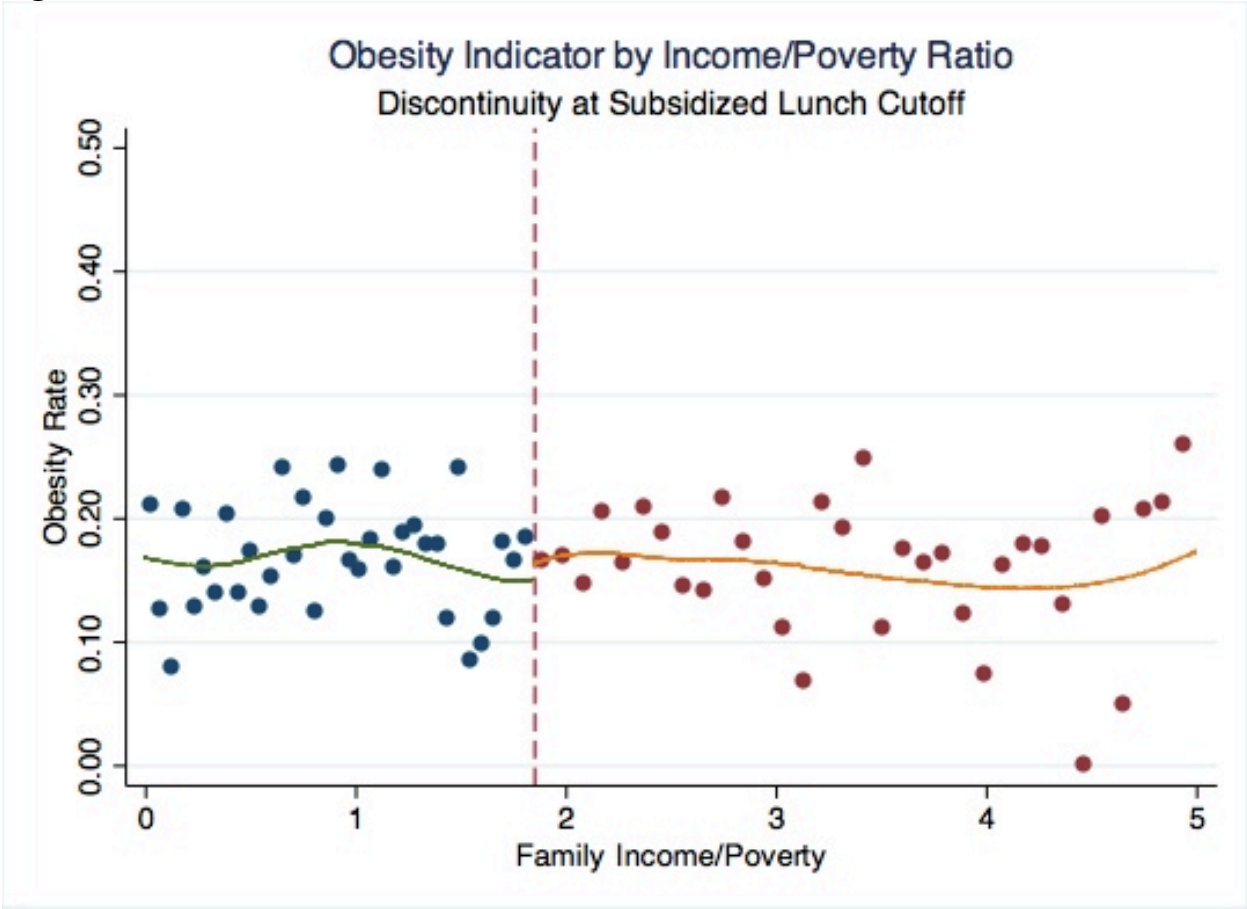


Figure 3.

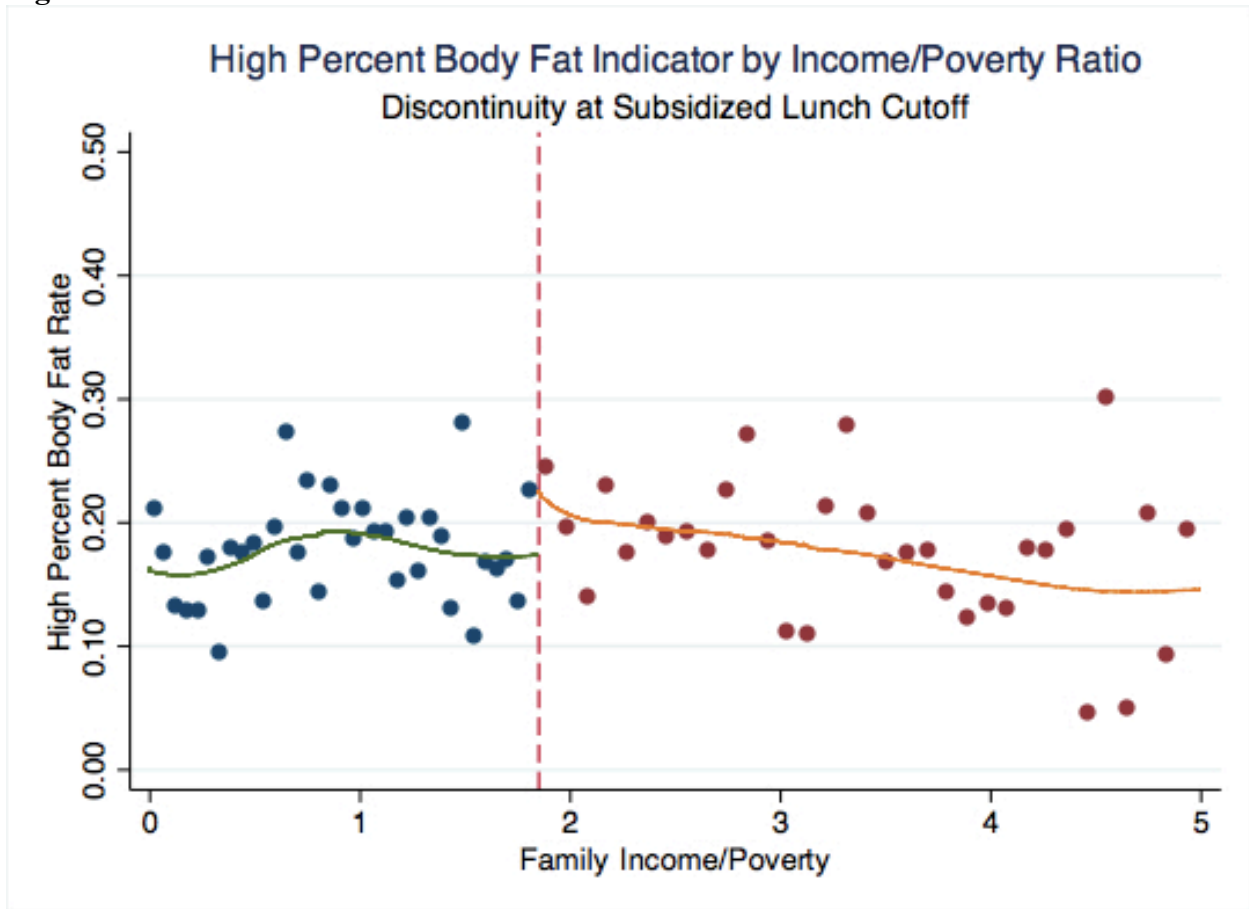


Figure 4.

