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THE INFLUENCE OF SCHOOL NUTRITION PROGRAMS ON THE WEIGHT OF LOW-INCOME CHILDREN: A TREATMENT EFFECT ANALYSIS

KRISTEN CAPOGROSSI[a,*] and WEN YOU[b]

[a]*RTI International, Research Triangle Park, USA*
[b]*Agricultural and Applied Economics, Virginia Tech, Blacksburg, USA*

ABSTRACT

Recent policy attempts to set high nutrition standards for the School Breakfast Program (SBP) and National School Lunch Program (NSLP) aim to improve children's health outcomes. A timely and policy-relevant task evaluates to what extent school meal programs contribute to child body mass index (BMI) outcomes to assess those school meal policies' potential impacts. This study examines children's weight progress from 1st through 8th grade, while recognizing the potential effects on those children participating in both programs compared with those children participating in only one program. We used difference-in-differences (DID) and average treatment effect on the treated (ATT) methodologies and focused on free- and reduced-price meal-eligible children to filter out income effects. The DID results show that short-term participation in only NSLP increases the probability that children will be overweight, and these results are more prominent in the South, Northeast, and rural areas. ATT results show that participation in both programs from 1st through 8th grade increases the probability that these students will be overweight. With the Community Eligibility Provision having taken effect across the nation in the 2014–2015 school year, the need to continue examining the impacts of these programs on child BMI is even greater.

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KEY WORDS: school nutrition programs; child weight; treatment effect analysis; School Breakfast Program; National School Lunch Program

1. INTRODUCTION

Many public programs and campaigns aim to prevent and fight childhood obesity by focusing on providing healthier school meals through the School Breakfast Program (SBP) and National School Lunch Program (NSLP). The U.S. Department of Agriculture (USDA) also made the Community Eligibility Provision—a provision of the Healthy Hunger-Free Kids Act that allows schools in high-poverty areas to provide free meals to all students—available to all states in the 2014–2015 school year. A USDA study on the first 2 years of the program found that the Community Eligibility Provision correlated with 'significantly higher student participation' in school meals (USDA, 2014). This fact introduces an even greater need to examine the impacts of these programs on child body mass index (BMI). Some work has found significant school influences on children's health outcomes, particularly child BMI (e.g., Briefel *et al*., 2009; Danielzik *et al*., 2005; James *et al*., 2007; Story *et al*., 2006), making such programs promising interventions for targeting child health issues.

As of 2014, more than 13.5 million students participated daily in SBP and 30.3 million participated daily in NSLP, and over 10.4 million and 21.2 million students received free- and reduced-price (FRP) breakfasts and

*Correspondence to: RTI International, 3040 Cornwallis Rd., Research Triangle Park, NC 27709, USA. 919-541-7330. E-mail: kcapogrossi@rti.org

lunches, respectively. The students receiving FRP meals are low-income students which we separate into participants who likely belong to families that are intermittently poor (i.e., experiencing short-term income fluctuation) and students who participate in the programs longer and are more likely to come from families that are persistently poor.

In addition to the large number of children served, research found that children consume one-third to one-half of their daily calories in school (Schanzenbach, 2009), particularly those children in low-income communities (Briefel *et al*., 2009). Therefore, policies supporting school meal programs can potentially affect a large number of children.

According to the Early Childhood Longitudinal Study-Kindergarten (ECLS-K) data used in our study,[1] approximately 25% of the students participated in the SBP and NSLP simultaneously at some point during their elementary or middle school tenure. With this sizable number of relevant students, it is important to know whether the different programs influence weight outcomes when children are served by both of these meal programs at the same time.

Results of investigating one program only could overstate/understate the impacts of that particular program when participation in another is ignored. Furthermore, potentially different self-selection into multiple programs versus a single program should be considered. Research has found that students who participated in both programs had different household and school characteristics than those who participated in only NSLP or neither program (e.g., Datar and Nicosia, 2009a, 2009b; Mirtcheva and Powell, 2009).

Furthermore, much of the research has only examined shorter-term impacts of the programs on child BMI (e.g., effects of participating for 1 to 3 years) (Schanzenbach, 2009; Millimet *et al*., 2010). To investigate the longer-term impact in a theoretically consistent way, we used an interdisciplinary theoretical framework that considers the features of a child's weight production to provide theory guidance in empirical investigation of both short- and long-term program effects.

2. RELATED LITERATURE SUMMARY

2.1. Impacts of SBP and NSLP

A key question that has been raised by both academia and the government is to what extent do SBP and NSLP contribute to the observed outcome of child BMI? The current literature has not yet reached a consensus, and this article aims to answer calls for further research (Schanzenbach, 2009; Economic Research Service (ERS), 2012; National Institutes of Health, 2012). Most of the existing work on SBP and NSLP has examined the nutritional quality of the food; the accessibility of the programs; and connections among program participation, nutrient intake, and child weight outcomes (e.g., Briefel *et al*., 2009; Cole and Fox, 2008). For instance, studies have found that NSLP participants consumed more of their calories at school from low-nutrient, energy-dense foods such as pizza (Briefel *et al*., 2009; Gordon *et al*., 2007). However, Fox *et al*. (2010) found no significant differences in overall diet quality between participants and nonparticipants. A gap in the literature is that the majority of the work has examined correlations that may merely reflect the impacts of other factors that simultaneously influence child BMI production, program eligibility, and program participation choice.

Some research has started to go beyond spurious correlation by considering that children who participated in the school meal programs may not be comparable to those who did not participate. Some research indirectly controls for selection bias (Schanzenbach, 2009), whereas other research models it directly (Millimet *et al*., 2010; Gundersen *et al*., 2012). However, the results on whether school meal programs affect child BMI are mixed in those studies. One reason is that those studies focused on different groups of students, limiting the comparability. In addition to covering the study sample differently, those studies did not consider the multiple

[1]We had Institutional Review Board approval from Virginia Tech on the study protocol. This is for data access and data safety.

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treatment effects of being simultaneously served by the two school meal programs and did not examine the longer-term impacts.

Our study has several unique aspects. First, we went beyond investigating single-program impacts to examine the impacts of participation in both programs simultaneously on children's weight. Second, we directly modeled school meal programs' participation based on a variety of child, family, and school characteristics; the model specification was guided by a theoretical model of child BMI production based on Capogrossi and You (2013). Third, we examined program impacts on child BMI through 8th grade to investigate potential long-term program effects.

2.2. Multiple overlapping treatments

The literature on multiple overlapping treatment effect analysis is minimal. As two of the pioneers of this type of analysis, Imbens (2000) and Lechner (2001) extended binary treatment effect analysis to multiple nonoverlapping treatments with two mutually exclusive treatments. This is similar to examining the impacts of SBP and NSLP on child BMI if children were allowed to participate in only one of the programs. However, examining multiple overlapping treatments considers the effects on children participating in both SBP and NSLP but without requiring participation in both programs. Lechner (2002) contributed one of the first empirical applications of multiple nonoverlapping treatments by examining mutually exclusive Swiss labor market policies. Cuong (2009) furthered the literature development by considering multiple overlapping treatments to examine the impacts of formal and informal credit in Vietnam using matching with difference-in-differences (DID).

Bradley and Migali (2012) allowed for overlapping treatments in a multilevel setting to study the impacts of two British policies on student test scores. Our article does not contribute to the multiple treatment literature methodologically; instead, it applies Bradley and Migali's (2012) techniques to child nutrition programs in the United States by using their average treatment effect on the treated (ATT) methodology to examine the impact of participating in two overlapping school meal programs on child BMI.[2]

3. CONCEPTUAL FRAMEWORK

When these data were collected, students had two ways of participating in the school meal programs: (i) children paid the full price for meals, or (ii) children were eligible for FRP meals.[3] At the beginning of each school year, schools send school meal applications home for parents to apply for FRP meals for their children.[4] However, a child may enroll for FRP school meals at any time throughout the school year by submitting a household application directly to the school. On the application, the parent provides information on the number of children in the household, sources of income, and contact information. The provided information will determine whether a child qualifies for FRP breakfast and lunch. Students qualify for free meals by having household income below 130% of the federal poverty line or between 131 and 185% of the poverty line for reduced-price meals. The free meal threshold therefore coincides with the federal SNAP limit. If a household receives SNAP benefits, TANF, or the Food Distribution Program on Indian Reservations, the children of the household automatically qualify for free school meals. The application is only good for the current school year.

Because participation in the school meal programs is mainly a parental decision with influences from the child (Gordon *et al*., 2007), we used the theoretical framework from Capogrossi and You (2013), which

[2]Details of the method are presented in the Empirical Issues and Strategies section of this paper.

[3]Now there is a third option with the Community Eligibility Provision (CEP), which is a provision from the Healthy Hunger-Free Kids Act of 2010 that allows schools and local educational agencies (LEAs) with high poverty rates to provide free breakfast and lunch to all students. CEP eliminates the burden of collecting household applications to determine eligibility for school meals, relying instead on information from other means-tested programs such as the Supplemental Nutrition Assistance Program (SNAP) and Temporary Assistance for Needy Families (TANF).

[4]Online applications are also available.

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employed a two-stage Stackelberg model to depict the interaction between parents and a child while permitting the child to have some input in household resource allocation decisions. The parents are modeled as the leader making household decisions, including program participation decisions, while taking into account the possible best responses of the child. The child is modeled as the follower and makes choices after observing parental decisions while knowing that his responses influence the observed parental allocations.

3.1. The child's optimization

Following Capogrossi and You's (2013) Stackelberg model, we used backward induction beginning with the child's optimization problem. Given what is available to her, the child makes choices regarding the amount of goods consumed that affect both BMI and utility (Rosenzweig and Schultz, 1983) (e.g., food and beverages) ($\boldsymbol{x_B}$) in addition to the amount of other consumption goods not affecting weight ($\boldsymbol{x_o}$) such as listening to music. The child also makes decisions regarding time spent in consuming all of these goods ($\boldsymbol{t_x}$), time spent on exercise ($\boldsymbol{t_E}$), and time spent on other activities ($\boldsymbol{t_o}$). Participation in the school meal programs serves as the overall treatment indicator (*SBP*, *NSLP*). The child BMI production function is as follows:

$$B = \boldsymbol{B}\left(\boldsymbol{x_B}, \boldsymbol{t_E}, \boldsymbol{t_X}; SBP, NSLP, \boldsymbol{I}, B_{t-1}, \boldsymbol{K_h^B}, \boldsymbol{K_s^B}, \boldsymbol{T_f}, \boldsymbol{\mu}\right). \tag{1}$$

Parental time spent in food preparation ($\boldsymbol{T_f}$) reflects the quality of food at home because the child's food choices are mainly reflected by the environment provided by the parents (e.g., Barlow and Dietz, 1998; Oliveria *et al*., 1992), and children's food preferences are partly shaped by observing their parents' food selections (e.g., Cutting *et al*., 1997). The school meal programs (*SBP*, *NSLP*) also provide a given set of food choices for the child, which is a good indicator for the school food environment (e.g., Briefel *et al*., 2009; Cole and Fox, 2008).

The child BMI production function also conditions on the child's weight outcome in the previous period (B_{t-1}) (Foster, 1995). This captures some of the genetic effects and unobserved environmental characteristics contributing to a child's past and current weight status (CDC, 2010). The production function also conditions on child characteristics ($\boldsymbol{\mu}$) as well as household $\left(\boldsymbol{K_h^B}\right)$ and school $\left(\boldsymbol{K_s^B}\right)$ environment characteristics affecting weight (Rosenzweig and Schultz, 1983). Weight inputs that do not augment child utility except through effects on weight are also included in the production function ($\boldsymbol{I}$) (e.g., health insurance, healthcare) (Briefel *et al*., 2009; Danielzik *et al*., 2005; Rosenzweig and Schultz, 1983).

The child's utility function depends on his current weight (B), consumption of goods ($\boldsymbol{x_B}$, $\boldsymbol{x_o}$), and his time allocations ($\boldsymbol{t_X}$, $\boldsymbol{t_E}$, $\boldsymbol{t_o}$); it is also conditional on school meal program participation (*SBP*, *NSLP*). Therefore, the child's utility function is as follows:

$$u = \boldsymbol{u}\left(B, \boldsymbol{x_B}, \boldsymbol{x_o}, \boldsymbol{t_X}, \boldsymbol{t_E}, \boldsymbol{t_o}; SBP, NSLP, \boldsymbol{K_h^B}, \boldsymbol{K_s^B}, \boldsymbol{T_f}, \boldsymbol{\mu}\right). \tag{2}$$

Utility maximization is subject to the child's weight production function (Equation 1) and a time constraint $\boldsymbol{t_X} + \boldsymbol{t_E} + \boldsymbol{t_o} = \boldsymbol{T}$, where T is the total amount of time. The optimal choice set of the child is, therefore, $\left(\boldsymbol{x_B^*}, \boldsymbol{x_o^*}, \boldsymbol{t_X^*}, \boldsymbol{t_E^*}, \boldsymbol{t_o^*}\right) = f\left(SBP, NSLP, \boldsymbol{I}, B_{t-1}, \boldsymbol{K_h^B}, \boldsymbol{K_s^B}, \boldsymbol{T_f}, \boldsymbol{\mu}\right)$, which is a function of parental choices, household and school environments, and other exogenous variables. Therefore, the child's indirect health production function is

$$B^* = \boldsymbol{B}\left(SBP, NSLP, \boldsymbol{I}, B_{t-1}, \boldsymbol{K_h^B}, \boldsymbol{K_s^B}, \boldsymbol{T_f}, \boldsymbol{\mu}\right). \tag{3}$$

Equation 3 is the main empirical equation that is investigated in this article, with a particular emphasis on examining the impacts of *SBP* and *NSLP* on B*.

3.2. The parent's optimization

The unitary model used assumes that there is one parent (i.e., the household head) acting as the main decision maker. The household head makes the decisions during the first stage of the game, including decisions about the child's school meal program participation. The household head's utility is affected directly by child's

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weight (B^*) and utility (u^*) as well as goods that the household head consumes ($\boldsymbol{Z}$), home and work environment characteristics ($\boldsymbol{K_h}$, $\boldsymbol{K_w}$), household head characteristics ($\boldsymbol{\phi}$), and household head's time allocations to work, food preparation, and other residual activities (T_w, T_f, T_o). The household head's utility function is

$$v = \boldsymbol{v}\left(\boldsymbol{Z}, \boldsymbol{T_w}, \boldsymbol{T_f}, \boldsymbol{T_o}, B^*, u^*; \boldsymbol{K_h}, \boldsymbol{K_w}, \boldsymbol{\varphi}\right), \tag{4}$$

which is subject to the household head's time constraint $T_w + T_f + T_o = T$ and budget constraint Y = P*M, where M is a vector of consumption goods M = M($\boldsymbol{Z}$, SBP, $NSLP$) , P is a vector of market prices associated with consumption goods $\boldsymbol{Z}$, as well as the prices for school meals, P = P($\boldsymbol{P_z}$, $\boldsymbol{P_{SBP}}$, $\boldsymbol{P_{NSLP}}$), and Y is total household income. Note that the child's school meal program participation status (SBP, $NSLP$) enters the household head's utility function indirectly through B^* and μ^*. The optimal household head choices are then functions of the exogenous variables in the model:

$$\left(SBP^*,\ NSLP^*,\ \boldsymbol{Z}^*,\ \boldsymbol{T}_j^*\right) = f(\boldsymbol{P},\ \boldsymbol{K_h},\ \boldsymbol{K_w},\ \boldsymbol{K_s},\ \boldsymbol{I},\ B_{t-1},\ \boldsymbol{\varphi},\ \boldsymbol{\mu}),\ \text{where}\ j = w,\ f,\ o. \tag{5}$$

Substituting the household head's optimal input demand functions (Equation set 5) into the child's indirect weight production function (Equation 3) yields the final reduced form equation for the child's weight outcome:

$$B^{**} = \boldsymbol{B}(\boldsymbol{I}, B_{t-1}, \boldsymbol{K_h}, \boldsymbol{K_s}, \boldsymbol{K_w}, \boldsymbol{p}, \boldsymbol{\mu}, \boldsymbol{\varphi}). \tag{6}$$

This article focuses on examining the impacts of SBP and NSLP participation on child BMI while directly controlling for self-selection into the programs. Both Equations 1 and 3 are valid candidates. We estimated Equation 3 because it demands less data (i.e., it does not require child's time use and consumption information). Furthermore, Equation set 5 provides the theoretical guidance in the instrumental variable selection and model specification that is necessary for controlling self-selection bias in a theoretically consistent way (Park and Davis, 2001).

4. EMPIRICAL ISSUES AND STRATEGIES

This section discusses the specific empirical challenges and analytical methodologies used. The main empirical challenges are to adequately control the differences among program participants and nonparticipants in the treatment effect estimations and to consider the overlapping multiple programs effects. We used two methodologies to assess the impact of SBP and NSLP participation on child BMI: DID and ATT.

4.1. Difference-in-differences estimation

We used the panel feature of the ECLS-K data set through DID with a matching methodology to examine the program transition effects. The data contain a subsample of children who switched school meal program participation status during their time in elementary and middle school (1st through 5th; 5th through 8th). The subsample provides data on the same individuals over time with and without treatment to allow further controlling of unobserved time-constant heterogeneity at the student level. Combining DID with matching has been found to perform the best in terms of eliminating potential sources of temporally invariant bias (Smith and Todd, 2005). While this methodology does not eliminate time-varying sources of program selection bias, this limitation is minimized in our context because of the delayed effect of food intake on health outcomes. DID is capturing short-term weight outcomes during which those time-varying behavioral changes may not take effect.

Using individual-level panel data with a treatment variable, the DID model is as follows with child weight (B^*) as the dependent variable:

$$B_{it}^* = \alpha + \beta_1 D_{it} + \delta_1 NSLP + \delta_2 BOTH + \gamma_1(D_{it} \cdot NSLP) + \gamma_2(D_{it} \cdot BOTH) + \beta_2 \boldsymbol{X}_{it} + \epsilon_{it.} \tag{7}$$

We included a time period dummy variable D_{it} (1st through 5th; 5th through 8th), two binary program indicators $NSLP$ and $BOTH$ (participation in both SBP and NSLP), two interaction terms between the time

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period and program indicators, and an unobservable error term ϵ_{it} in addition to covariates $\boldsymbol{X}_{it}$. From this model, γ_1 and γ_2 are our program treatment effects relative to no program participation that takes into consideration trends over time for both participants and eligible nonparticipants.

4.2. Treatment effect estimation

4.2.1. Choice of treatment effect measures. Two aforementioned studies (Millimet *et al.*, 2010; Gundersen *et al.*, 2012) examined the school meal programs' average treatment effect (ATE) on child BMI. The ATE is most relevant if a policy exposes every individual to the treatment or none at all (Imbens and Wooldridge, 2009). In contrast, ATT examines program effects on a well-defined population exposed to the treatment or effects of a voluntary program where individuals are not obligated to participate (Imbens and Wooldridge, 2009):

$$\tau_{ATT} \equiv E[B^*(1) - B^*(0)|NSLP = 1]. \tag{8}$$

Equation 8 shows that the ATT captures the average program effects on child weight (B^*) for those who actually participated in the NSLP (NSLP = 1). The ATT is more relevant to our case: we are interested in the effect of participation on those low-income children who choose to participate in SBP and/or NSLP where opt-out is always an option.

4.2.2. Two-step multiple treatment effect analysis. The ATT estimator considers two distinct effects: the program treatment effect and the selection effect (which is the factor that causes systematic differences among program participants and nonparticipants) (Geneletti and Dawid, 2011). The literature has shown evidence of the school meal programs' selection effects (Dunifon and Kowaleksi-Jones, 2003; Mirtcheva and Powell, 2009). Even modest amounts of positive selection can eliminate or reverse potential program impacts on child BMI (Millimet *et al.*, 2010).

This study follows Bradley and Migali (2012) to conduct a multiple treatment analysis that considers the propensity to participate in one or both school meal programs in the first stage and then matches the propensity scores for the treated and untreated groups using caliper matching.[5] Once the propensity scores for each student have been obtained, the validity of results depends on the quality of matches based on observed characteristics. Matching does not take into consideration unobservable sources of bias. Two matching algorithms were used to assess the robustness of the results: (i) caliper matching with replacement with radii of 0.01 and common support of 2% (i.e., dropping 2% of the treatment observations that have the lowest match with its control) and (ii) nearest neighbor matching.[6] Controlling for simultaneous participation in multiple treatments (e.g., using multinomial logit rather than a series of binary models) makes matching more efficient with regard to the mean square error (Cuong, 2009).

We created a categorical variable to reflect the three participation statuses:

1. No program participation over the entire period (s = 0)
2. NSLP participation only over the entire period (s = 1)
3. SBP and NSLP participation over the entire period (s = 2)

'Entire period' refers to all the grades for which data were collected (1st, 3rd, 5th, and 8th grades). For example, if a child falls into the category $s = 0$, then he did not participate in either school meal program in 1st, 3rd, 5th, or 8th grade. Note that we do not have the category of SBP participation only because our data set contains very few children who only participate in SBP (about 1% of the sample). Those three program

[5]Caliper matching uses a predefined tolerance level on the maximum propensity score distance between matches. Treated observations are matched with nearest neighbor control observations within that caliper to avoid poor matches (Becker and Ichino, 2002).
[6]Using two different algorithms for matching provides a sensitivity analysis for the models. Only results using the caliper matching are presented.

participation statuses are mutually exclusive, and the conditional probability (CP) of choosing one of the three is:

$$CP^{s/S} = CP^{s/S}(S = s|X = x, S \in \{s\}) = \frac{CP^s(x)}{CP^S(x) + CP^s(x)}, \text{ where } s \in S. \tag{9}$$

Guided by the previously discussed Equation set 5, the program selection propensity estimation controlled for the following covariates: child's gender ($\boldsymbol{\mu_{gender}}$), race/ethnicity ($\boldsymbol{\mu_{race}}$), weight in the previous period (B_{t-1}), household income ($\boldsymbol{K_h}$), parents' education levels (ϕ), whether the mother works full time (ϕ), whether the parents are married ($\boldsymbol{K_h}$), and urbanicity ($\boldsymbol{K_s}$).

The second stage of the treatment effect analysis is to use the propensity scores estimated in the first stage to conduct propensity score matching (PSM), which matches treated and untreated observations that are as similar as possible in an attempt to control for potential selection effects based on observables. Common support ensures that persons with the same observable values have a positive probability of being both participants and nonparticipants. Furthermore, matching should balance characteristics across the treatment and matched comparison groups. This can be examined by inspecting the distribution of the propensity score in the treatment and matched comparison groups. Hence, using PSM with strong support and good balance, we can interpret results as the mean effect of program participation based on observables. Time-varying sources of bias as a source for selection bias may still exist.

4.2.3. Rosenbaum bounds. Over the past several years, matching has become a frequently used method for estimating treatment effects in observational data (Keele, 2010). PSM takes into account selection based on observables but not unobservables. To investigate the sensitivity of our results, we calculated Rosenbaum bounds to examine the influence of unobservables (Joffe and Rosenbaum, 1999). Rosenbaum bounds allow us to determine how strong the influence of unobservables must be on the selection process to weaken the results of the matching analysis (Becker and Caliendo, 2007). Rosenbaum's sensitivity analysis for matched data provides information about the magnitude of hidden bias that would need to be present to explain the associations actually observed (Rosenbaum, 2005). The analysis relies on the sensitivity parameter Γ, which measures the degree of departure from random assignment of treatment. Two subjects with the same observed characteristics may differ in the odds of receiving the treatment by at most a factor of Γ. In a randomized experiment, randomization of the treatment ensures that $\Gamma = 1$. In an observational study, if $\Gamma = 2$ and two subjects are identical on matched covariates, then one subject might be twice as likely as the other to receive the treatment because they differ in terms of an unobserved covariate (Rosenbaum, 2005). There is hidden bias if two subjects with the same matched covariates have differing chances of receiving the treatment. Specifically to examine the Rosenbaum bounds, we used the Mantel and Haenszel (1959) statistic. This statistic compares the number of 'successful' subjects in the treatment group with the number of 'successful' subjects from the control group after controlling for covariates (Becker and Caliendo, 2007).

5. DATA AND DESCRIPTIVE STATISTICS

We used data from ECLS-K, which is a longitudinal study of a nationally representative cohort of 21,260 children beginning kindergarten in the 1998–1999 school year and who were followed through 8th grade in the 2006–2007 school year.[7] Conducted by the National Center for Education and Statistics, the study collected data on children in over 1000 different schools, as well as on their families, teachers, and school

[7]We realize that these data are older; however, the 8th grade data were not publicly available until 2010. The National Center for Education and Statistics is currently collecting data on a new cohort of children who started kindergarten in the 2010–2011 school year and following them through 8th grade. So far, only the kindergarten and 1st grade data have been made publicly available. Therefore, this time range of the data is the only one that meets the data demand for our research purpose.

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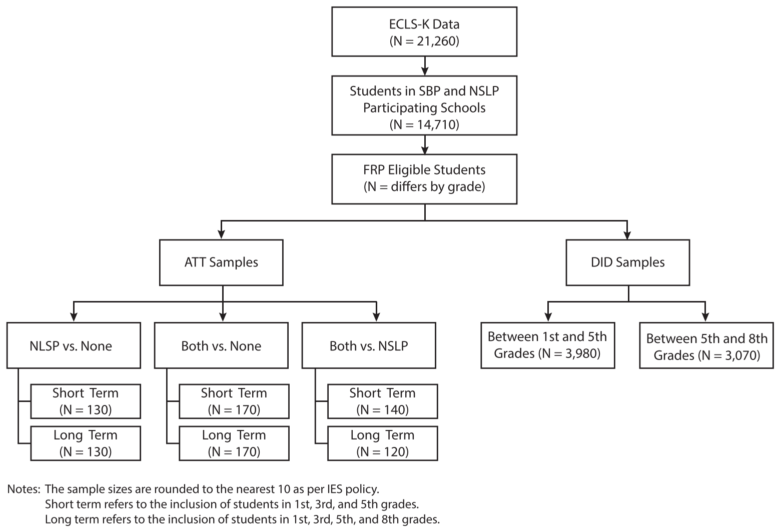

Figure 1. Flow chart of the analyzed samples. Notes: The sample sizes are rounded to the nearest 10 per IES policy. Short term refers to the inclusion of studies in the 1st, 3rd, and 5th grades. Long term refers to the inclusion of students in the 1st, 3rd, 5th, and 8th grades

facilities/characteristics, including measures of children's physical health and growth, social and cognitive development, and emotional well-being.[8] Seven waves of the study were administered—fall and spring of kindergarten; the springs of 1st, 3rd, 5th, and 8th grades; and a small subsample of children in the fall of 1st grade to obtain information on the summer activities of the children.

5.1. Sample selection

Figure 1 shows a flow diagram of our sample selection. The ECLS-K data followed a nationally representative cohort of 21,260 children, which is the sample size pool for this study. First, we eliminated students who attended schools that did not participate in both SBP and NSLP, which narrowed the sample size to 14,710 children. Next, we considered only those students who were eligible for FRP meals—students whose parents reported a household income at or below 185% of the poverty level—which varied by grade level because household income varied from year to year.[9] Our study used two types of analyses—DID and ATT—for which we used different samples. For the DID samples, we examined those students who switched participation status between 1st and 5th grade and those students who switched participation status between 5th and 8th grade. For the ATT, we examined short-term (1st through 5th grade) and long-term (1st through 8th grade) participants in three categories: those students only participating in NSLP compared with no participation, those students participating in both SBP and NSLP compared with no participation, and those students participating in both SBP and NSLP compared with only NSLP participation.[10]

5.2. Data generation overview

Equation 3 is the structural child BMI production function and is the key equation of interest for this paper. Child BMI (B) was objectively measured at each data collection point: the height (in inches to the nearest

[8]Details of the data collection and instruments can be found in the *Early Childhood Longitudinal Study*, *Kindergarten Class of 1998–1999 User's Manual* (Tourangeau *et al*., 2009).
[9]Since our sample only includes those students who are eligible for free- and reduced-price lunch, it excludes those who pay full-price for school lunch. When considering all students, approximately 69% of the students in the ECLS-K data participate in NSLP.
[10]These sample sizes are rounded to the nearest 10 per Institute of Education Sciences (IES) policy.

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quarter-inch) and weight (in pounds to the nearest half-pound) measurements were recorded by the assessor using the Shorr Board and a Seca digital bathroom scale, respectively, and all children were measured twice to minimize measurement error. We used a continuous measure (BMI z-score[11]) and dichotomous quantifiers of child weight status (i.e., overweight or normal weight) calculated according to CDC standards (Centers for Disease Control and Prevention (CDC), 2009). A total of 320 observations were dropped because they were biologically implausible.[12]

The two key independent variables of interest are SBP and NSLP participation status indicators, which are available from parent and school administrator surveys. Parents were asked if the school provides breakfast and lunch to students, if the child eats a school breakfast and/or lunch, and if the child receives FRP breakfasts and lunches. School administrators were asked the percentage of FRP lunch-eligible students in the school. Based on the theoretical model and previous literature, the child's weight status in the previous period is accounted for (B_{t-1}), and home environment characteristics $\left(\boldsymbol{K}_h^B\right)$ include the parents' education levels, the mother's employment status, whether the parents were married, household income, urbanicity, how many days per week the family ate meals together, and whether the household was food secure.[13]

The school level characteristics $\left(\boldsymbol{K}_s^B\right)$ include the percentage of students eligible for FRP meals, an indicator for whether the school was Title I, and the number of students enrolled in the school. The survey did not take any direct measures of parental time spent in food preparation ($\boldsymbol{T_f}$), but this variable is indirectly controlled for by including the number of days per week the family ate breakfast and dinner together as covariates. Child characteristics ($\boldsymbol{\mu}$) include gender, age, race/ethnicity, and birth weight in ounces.

5.3. Descriptive statistics

Summary statistics are presented in Table I by grade level and meal program participation status over time.[14] Our sample shows similar trends as found in the literature: on average, household income is lower and the proportion of food insecurity is higher for students participating in both programs compared with students participating in only one program or no program. On average, there do not seem to be statistically significant differences in weight (both BMI z-scores and weight classification proportions) between participants and nonparticipants. More black, Hispanic, and rural students participated in both meal programs than did not participate. Higher proportions of students participating in both meal programs came from families experiencing food insecurity than nonparticipating students.

6. RESULTS

Following the order of the methods section, we present the short-term results from the DID with matching followed by the short-term and long-term multiple treatment effect analysis of the ATT results. All analyses were conducted for low-income children eligible for FRP meals. Each of these analyses provides insights on different subsets of children to give a more complete picture of how the SBP and NSLP affect the weight of low-income students. The DID estimation sample consists of students who switched program participation

[11]We report BMI z-scores, which are the internationally accepted continuous measure of BMI that are particularly useful in monitoring changes in weight. A BMI-for-age z-score is the deviation of the value for a child from the mean value of the reference population divided by the standard deviation for the reference population (Cole *et al*., 2005).

[12]The CDC program provided criteria for children's BMIs that should be considered to be 'biologically implausible values' based on the World Health Organization's fixed exclusion ranges.

[13]There may be some concern regarding potential endogeneity between food security and child BMI; however, we conducted analyses with and without this variable and the results remain robust.

[14]All analyses in the paper used sample weights, which produced estimates that were representative of the population cohort of children who began kindergarten in 1998–1999. The sample weight used was C1_7FP0.

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Table I. Summary statistics for sample by grade and meal program participation status

Variable	Description	NSLP Only			SBP and NSLP			No participation		
		1st	5th	8th	1st	5th	8th	1st	5th	8th
Obese	=1 if child is obese	0.14 (0.35)	0.24 (0.42)	0.21 (0.41)	0.18 (0.38)	0.25 (0.43)	0.22 (0.42)	0.15 (0.36)	0.23 (0.42)	0.22 (0.41)
Overweight	=1 if child is overweight	0.12 (0.33)	0.17 (0.38)	0.15 (0.35)	0.12 (0.32)	0.16 (0.37)	0.17 (0.37)	0.13 (0.33)	0.15 (0.36)	0.16 (0.37)
Healty weight	=1 if child is healthy weight	0.63 (0.48)	0.50 (0.50)	0.53 (0.50)	0.61 (0.49)	0.50 (0.50)	0.48 (0.50)	0.64 (0.48)	0.55 (0.50)	0.54 (0.50)
Current BMI	BMI *z*-score	0.41 (1.14)	0.70 (1.15)	0.69 (1.12)	0.58 (1.13)	0.75 (1.12)	0.81 (1.04)	0.50 (1.07)	0.58 (1.22)	0.75 (1.05)
Previous BMI	BMI *z*-score in previous period	0.40* (1.17)	0.62 (1.16)	0.70 (1.17)	0.52** (1.27)	0.67 (1.09)	0.77 (1.10)	0.30 (1.19)	0.58 (1.19)	0.68 (1.18)
Female	=1 if child is female	0.48 (0.50)	0.50 (0.50)	0.51 (0.50)	0.49 (0.50)	0.48 (0.50)	0.47** (0.50)	0.45 (0.50)	0.50 (0.50)	0.57 (0.50)
Black	=1 if child is black	0.13 (0.33)	0.12 (0.33)	0.12 (0.33)	0.24*** (0.43)	0.24*** (0.43)	0.27*** (0.44)	0.09 (0.29)	0.12 (0.32)	0.07 (0.26)
Hispanic	=1 if child is Hispanic	0.23* (0.42)	0.26** (0.44)	0.24 (0.43)	0.29*** (0.45)	0.30*** (0.46)	0.33 (0.47)	0.17 (0.37)	0.18 (0.38)	0.26 (0.44)
Rural	=1 if lives in rural area	0.34** (0.47)	0.35** (0.48)	0.38** (0.49)	0.39*** (0.49)	0.37*** (0.48)	0.35* (0.48)	0.26 (0.44)	0.25 (0.44)	0.27 (0.45)
Urban	=1 if lives in urban area	0.36 (0.48)	0.36 (0.48)	0.31 (0.46)	0.36 (0.48)	0.38 (0.49)	0.38 (0.49)	0.40 (0.49)	0.39 (0.49)	0.36 (0.48)
TV	Minutes per day child watches TV	131.39 (76.07)	140.51 (71.19)	198.40 (179.06)	145.80*** (94.02)	150.11 (86.43)	227.51 (219.53)	123.45 (63.19)	138.22 (75.71)	196.64 (166.79)
Active	Days per week child participates in 20 minutes of activity (sweats)	4.13 (2.28)	3.66 (1.87)	5.26 (1.80)	3.93 (2.51)	3.70 (2.11)	5.06 (1.89)	3.99 (2.30)	3.68 (1.86)	5.23 (1.72)
Household income	on scale 1–9	3.45*** (1.17)	3.52*** (1.22)	3.60*** (1.17)	2.60*** (1.16)	2.80*** (1.18)	2.87*** (1.18)	3.97 (1.03)	4.00 (0.95)	3.84 (1.09)
Mom full time	=1 if mother works full-time	0.48 (0.50)	0.51 (0.50)	0.59 (0.49)	0.50 (0.50)	0.50 (0.50)	0.51 (0.50)	0.48 (0.50)	0.52 (0.50)	0.54 (0.50)
Breakfasts	Number of breakfasts eaten per week as a family	4.40*** (2.46)	3.57*** (2.47)	3.18 (2.30)	3.16*** (2.14)	2.51*** (2.02)	2.44*** (1.79)	4.45 (2.38)	2.98 (2.25)	3.04 (2.32)
Dinners	Number of dinners eaten per week as a family	5.83 (1.69)	5.59 (1.75)	5.40 (1.78)	5.91 (1.72)	5.65 (1.76)	5.58** (1.77)	5.72 (1.67)	5.42 (1.82)	5.22 (1.69)
Food insecure	=1 if family is food insecure	0.10 (0.30)	0.12 (0.33)	0.13* (0.33)	0.19*** (0.39)	0.24*** (0.43)	0.24*** (0.43)	0.08 (0.26)	0.09 (0.29)	0.07 (0.26)
N		920	790	750	1,050	1,030	930	180	140	120

Note: Standard deviations are in parentheses.
*Indicates statistically different from no participation at the 10% level.
**Indicates statistically different from no participation at the 5% level.
***Indicates statistically different from no participation at the 1% level.
Sample sizes are rounded to the nearest 10 per IES policy.

status and who likely belonged to those families that are intermittently poor (i.e., experiencing short-term income fluctuation) while the ATT sample consists of students who participated in the programs longer and were more likely to come from families that are persistently poor.

6.1. Difference-in-differences results

We used DID estimation to examine the program impacts on low-income students who changed program participation status from 1st through 5th grade and 5th through 8th grade. This group of students is important to study because they likely belong to families that are intermittently poor—an increase or decrease in family income probably caused the student to not participate or participate in FRP meals. These students may have different household characteristics than the students who participate in the programs their whole school career.

When examining students switching participation status, some evidence suggests that switching into the school meal programs increases BMI z-scores and the probability of overweight (Table II). For example, those students entering only NSLP in 5th grade have a statistically significant increased probability of being overweight. The coefficient on BMI z-score is also positive and statistically significant. In addition, students entering both programs in 8th grade have a statistically significant increased probability of being overweight and a decreased probability of being healthy weight. These results indicate that there is a relationship between meal program participation and child weight based on observable and time-invariant characteristics. Time-varying sources of bias potentially still remain as a source for selection bias using this methodology; however this limitation is minimized in our context because of the delayed effect of food intake and health outcomes: in other words, those time-varying behavioral changes may not affect short-term weight outcomes which is what DID is capturing.

6.2. Average multiple treatment effect on the treated results

We also examined the following program impacts on weights of those program-eligible children who consistently participated in school meal(s) from 1st through 5th and 1st through 8th grade: (i) students who participated in only NSLP relative to no program participation; (ii) students who participated in both programs relative to no program participation; and (iii) students who participated in both programs relative to only NSLP participation. Students who participate in the program(s) consistently are important to study because they likely belong to families that are persistently poor rather than intermittently poor.

The covariates used in the matching are data collected when the child was in kindergarten because those can be considered pretreatment variables.[15] To examine the validity of the treatment effect estimators, we checked covariate balance, bias reduction, and common support between groups (Caliendo and Kopeinig, 2005). Figure 2 illustrates the balance results of this examination. As the figure shows, PSM reduces the observable bias across covariates. For the most part, the balance graphs show a sizable reduction of the standardized percent bias across covariates. In terms of common support, less than 3% of observations were off support when comparing only NSLP participation with no participation, and less than 4% of observations were off support when comparing both SBP and NSLP participation with no program participation. However, this analysis cannot control for what those participating children consume outside of school or at home, and these

[15]We matched on the following characteristics from the kindergarten data collection round: gender, race/ethnicity, baseline BMI, household income, mother's education, whether the mother works full time, whether the parents are married, urbanicity, whether the household has received SNAP within the last 12 months, and the percentage of children within the school eligible for free lunch.

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Table II. Difference-in-difference results on 5th and 8th grade child BMI

Weight outcome	Between 1st and 5th grade		Between 5th and 8th grade	
	NSLP only	SBP and NSLP	NSLP only	SBP and NSLP
BMI *z*-score	0.129** (0.06)	−0.052 (0.05)	−0.008 (0.06)	0.021 (0.06)
Overweight/obese	0.059* (0.03)	0.019 (0.06)	0.051 (0.04)	0.086** (0.04)
Normal weight	−0.044 (0.04)	0.006 (0.04)	−0.053 (0.04)	−0.071* (0.04)
N	1840	2140	1420	1650

*Indicates statistically significant at the 10% level.
**Indicates statistically significant at the 5% level.
Standard errors are in parentheses.
BMI = body mass index.
NSLP = National School Lunch Program.
SBP = School Breakfast Program.
Results include the following covariates: gender, race, age, birth weight, past BMI, number of children enrolled at the school, whether the school is Title I, the percentage of children eligible for FRP meals, mother's education level, father's education level, whether the mother works full time, whether the parents are married, household income, urbanicity, number of breakfasts and dinners the family eats together, and whether the household is food insecure.
Unweighted sample sizes are rounded to the nearest 10 per IES policy.

unobservables would affect body mass outcomes. Furthermore, a child's behaviors related to calorie consumption are likely to be associated with nurturing environment.

The short-term and long-term ATT results are presented in Table III. Results show that participation in school meal programs has no statistically significant effect on short-term (participating from 1st through 5th grade) child weight. However, long-term participation (participating from 1st through 8th grade) has a larger impact. Participating in both SBP and NSLP from 1st through 8th grade increases the probability of overweight at a statistically significant level. If the child participates in only NSLP over the same period, she has a lower probability of being overweight. Furthermore, when comparing participation in both programs to only participation in NSLP, the child has a statistically significant lower probability of being in the normal weight range. These results indicate that additional research is needed on the impacts of the SBP separately from the NSLP. The findings are similar to the DID findings in that results are manifested in the 8th grade. This finding also could indicate that the food choices offered in middle school compared with elementary school rather than length of participation may have an impact on child weight.

To investigate the robustness of our results, we calculated Rosenbaum bounds, specifically the Mantel and Haenszel statistic, to examine the influence of unobservables. The Mantel and Haenszel *p*-values of meal program participation on child weight outcomes for 5th and 8th graders who had been participating in school meal programs from 1st grade are presented in Table IV. Gamma is the odds of differential assignment because of unobserved factors. The matching results show that the overweight/obese coefficient of participating in both programs compared with NSLP from 1st through 8th grade (0.267) and participating in both programs compared with none (0.231) were significant. We find these results to be somewhat robust: these outcomes are insensitive to a bias for the current odds of program participation. However, if you increased the odds of program participation for the students in each of these samples to two or three times the current odds, the results are no longer robust. We do find insensitivity for the normal weight coefficients in the 8th grade for those students who participate in both SBP and NSLP, making the normal weight coefficient for those students participating in both programs compared with NSLP (−0.299) robust.

Because numerous variables affect child weight, many of which are not observed in the data, it is not surprising that there is some influence of unobservables in the model. To decrease the influence, additional predictors of child weight would need to be accounted for such as the parents' weight, more accurate indicators of physical activity, and food consumed at home. The ECLS-K did not collect data on these variables.

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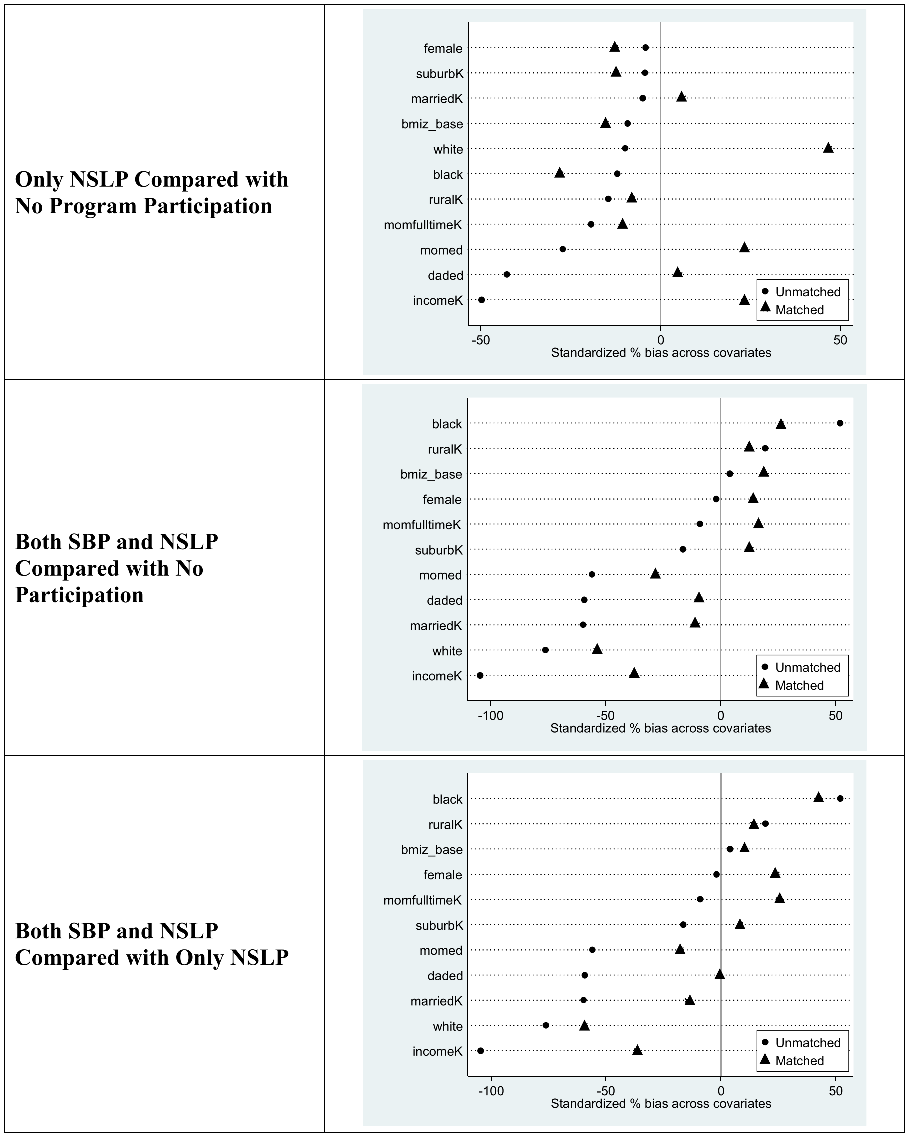

Figure 2. Series of balance graphs for PSM for FRP-eligible students

6.3. Subgroup analyses

To check the above conclusions' robustness, we examined three subgroups using the DID method: (i) analyzing impacts on child BMI controlling for food expenditures by LEA;[16] (ii) examining impacts on child BMI by

[16]We link the ECLS-K data to the Common Core of Data (CCD). The CCD is a comprehensive, annual, national statistical database of all public elementary and secondary schools and school districts in the United States. It also provides descriptive statistics on the schools, as well as fiscal and nonfiscal data, including expenditures on food services. Expenditures on food services are described as 'gross expenditure for cafeteria operations to include the purchase of food but excluding the value of donated commodities and purchase of food service equipment.' Using LEA data is more appropriate than school-level data because meal programs are regulated at the district level, and LEAs allocate funding. Controlling for average food expenditures per pupil provides an indicator of food quality because research shows that healthier food is more costly than nutrient-dense food (Cade *et al*., 1999; Darmon *et al*., 2004; Drewnowski, 2004; Drewnowski and Specter, 2004; Kaufman *et al*., 1997; Stender *et al*., 1993). We used the CCD's expenditures on food services variable and divided it by the CCD's school system enrollment variable because the data provides exact enrollment and included per-pupil food expenditures as an additional covariate in our DID models.

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Table III. Short-term and long-term ATT results for single and multiple treatment effects on child BMI

	From 1st to 5th grade			From 1st to 8th grade		
Weight outcome	NSLP vs. None[1]	Both vs. None[1]	Both vs. NSLP[2]	NSLP vs. None[1]	Both vs. None[1]	Both vs. NSLP[2]
Normal weight	0.059 (0.10)	−0.043 (0.11)	0.020 (0.11)	0.121 (0.10)	−0.164 (0.11)	−0.299** (0.12)
Overweight/ obese	−0.134 (0.10)	0.097 (0.10)	−0.007 (0.11)	−0.176** (0.09)	0.231** (0.09)	0.267*** (0.10)
N	130	170	140	130	170	120

[1]Examine impacts on different child BMI classifications of (1) only NSLP participation compared with no participation and (2) SBP and NSLP participation compared with no participation.
[2]Examine impacts on different child BMI classifications of SBP and NSLP participation compared with only NSLP participation.
*Indicates statistically significant at the 10% level.
**Indicates statistically significant at the 5% level.
***Indicates statistically significant at the 1% level.
We examined relative impacts of single and multiple treatment effects with 5th and 8th grade weight status as the outcome variable. The standard errors are in parentheses. Results are reported for radius/caliper matching of 0.01 trimming common support at 2%.
ATT = average treatment effect on the treated.
BMI = body mass index.
NSLP = National School Lunch Program.
SBP = School Breakfast Program.
Unweighted sample sizes are rounded to the nearest 10 per IES policy.

dividing the sample based on urbanicity; and (iii) examining impacts on child BMI by dividing the sample based on region.

First, we controlled for the impact of per-pupil food expenditures by LEA. We realize that spending a lot of money on meals does not necessarily guarantee a meal's quality. However, the School Nutrition Association found in their *2013 Back to School Trends Report* that more than 9 out of every 10 school districts reported increases in food costs in trying to meet the new school nutrition standards of the Healthy Hunger-Free Kids Act. This cost increase indicates a potential quality change in school meals with increased spending.

We found very similar results in significance and magnitude to the initial DID results, as Table V shows. BMI *z*-scores increase as does the probability of being overweight at a statistically significant level for those participating in only NSLP in 5th grade. Furthermore, participation in both programs increases the probability of being overweight in 8th grade at a similar magnitude and level of significance as the initial DID results.

Next, we examined whether urbanicity has an impact on the outcome of child BMI because research shows that children living in rural areas tend to have higher participation rates in school meal programs (Wauchope

Table IV. Mantel–Haenszel p-values (p_MH+) for students in 5th and 8th grades

		1st to 5th grade		1st to 8th grade	
	Gamma	Overweight	Normal	Overweight	Normal
NSLP vs. none	1	0.229	0.421	0.025	0.161
	2	0.004	0.087	0.000	0.319
	3	0.000	0.006	0.000	0.060
Both vs. none	1	0.156	0.540	0.010	0.050
	2	0.284	0.039	0.240	0.000
	3	0.044	0.001	0.583	0.000
Both vs. NSLP	1	0.262	0.503	0.008	0.054
	2	0.196	0.028	0.179	0.000
	3	0.025	0.001	0.468	0.000

Null hypothesis is overestimation of the treatment effect; rejecting the null means we do not suspect overestimation.
NSLP = National School Lunch Program.

Table V. Difference-in-difference results on 5th and 8th grade child BMI controlling for LEA food expenditures

	5th grade		8th grade	
Weight outcome	NSLP only	SBP and NSLP	NSLP only	SBP and NSLP
BMI *z*-score	0.114* (0.06)	0.013 (0.06)	−0.010 (0.06)	0.022 (0.06)
Overweight/obese	0.064* (0.03)	0.012 (0.03)	0.042 (0.04)	0.082** (0.04)
Normal weight	−0.053 (0.04)	−0.001 (0.04)	−0.042 (0.04)	−0.065 (0.04)
N	1,820	2,100	1,400	1,620

*Indicates statistically significant at the 10% level.
**Indicates statistically significant at the 5% level.
***Indicates statistically significant at the 1% level.
Standard errors are in parentheses.
BMI = body mass index.
LEA = local educational agency.
NSLP = National School Lunch Program.
SBP = School Breakfast Program.
Results include the following covariates: gender, race, age, birth weight, past BMI, number of children enrolled at the school, whether the school is Title I, the percentage of children eligible for FRP meals, mother's education level, father's education level, whether the mother works full time, whether the parents are married, household income, urbanicity, number of breakfasts and dinners the family eats together, and whether the household is food insecure.
Unweighted sample sizes are rounded to the nearest 10 per IES policy.

and Shattuck, 2010) and higher rates of overweight and obesity (Datar *et al*., 2004; Wang and Beydoun, 2007), which could be suggestive of the nutritional quality differences of foods consumed. We found the largest significant program effect is on those students living in rural areas (Table VI). For the income-eligible students living in rural populations, we found similar results to the initial findings for the NSLP-only participants in 5th grade: these low-income participants have a statistically significant higher probability of being overweight and a statistically significant higher BMI *z*-score. In addition, these students living in a rural area have a statistically significant lower probability of being in the normal weight range. Additionally, there are no statistically significant impacts on children living in urban areas.

Finally, we examined regional differences (i.e., Northeast, Midwest, South, and West) because the cuisine across the United States is diverse—each region has a distinct style that could influence the types of food served at school (Kulkarni, 2004; Smith, 2004). We found that the school meal programs have the most significant impact on child weight in the South and Northeast, particularly on 5th grade child BMI in the South and 8th grade child weight in the Northeast. Participating in only NSLP increases the probability of overweight for 5th grade participants in the South, as Table VII indicates. The magnitude is nearly double the magnitude of the initial results, indicating a larger impact in the South. There is also a statistically significant impact on 8th grade child weight for those students participating in both school meal programs in the Northeast. The sign of the coefficient is the same as initial results, but the magnitude is nearly double: participating in both programs increases the probability of overweight and decreases the probability of normal weight. These results indicate that region of participation may also play a role in whether the programs contribute to child overweight.

7. CONCLUSIONS AND POLICY IMPLICATIONS

In this paper, we examine the impacts of school meal program participation on child weight development. This study contributes to the literature by conducting a multiple overlapping treatment effect analysis while accounting for observable and time-invariant self-selection into the programs. Specifically, we used DID and ATT methodologies for our treatment analysis to examine students who switch participation status (DID) and those who consistently participate in programs (ATT). To provide empirical specification guidance for dealing with self-selection bias, we used Capogrossi and You's (2013) theoretical model incorporating program participation decisions.

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Table VI. Difference-in-difference results on 5th and 8th grade child BMI

	Rural				Urban			
	5th grade		8th grade		5th grade		8th grade	
Weight outcome	NSLP only	SBP and NSLP	NSLP only	SBP and NSLP	NSLP only	SBP and NSLP	NSLP only	SBP and NSLP
BMI *z*-score	0.412*** (0.12)	0.130 (0.09)	−0.045 (0.10)	−0.168** (0.08)	0.111 (0.11)	0.008 (0.12)	−0.019 (0.12)	0.098 (0.13)
Overweight/obese	0.143** (0.06)	0.064 (0.05)	0.040 (0.06)	0.021 (0.06)	−0.002 (0.06)	−0.026 (0.06)	0.045 (0.08)	0.054 (0.07)
Normal weight	−0.090* (0.06)	−0.068 (0.06)	−0.018 (0.07)	0.006 (0.07)	0.031 (0.07)	0.049 (0.07)	−0.041 (0.09)	−0.053 (0.08)
N	670	840	560	650	600	690	410	520

*Indicates statistically significant at the 10% level.
**Indicates statistically significant at the 5% level.
***Indicates statistically significant at the 1% level.
Standard errors are in parentheses.
BMI = body mass index.
NSLP = National School Lunch Program.
SBP = School Breakfast Program.
Results include the following covariates: gender, race, age, birth weight, past BMI, number of children enrolled at the school, whether the school is Title I, the percentage of children eligible for FRP meals, mother's education level, father's education level, whether the mother works full time, whether the parents are married, household income, urbanicity, number of breakfasts and dinners the family eats together, and whether the household is food insecure.
Unweighted sample sizes are rounded to the nearest 10 per IES policy.

Table VII. Difference-in-difference results on 5th and 8th grade child BMI for participants by region

	South				Northeast			
	5th grade		8th grade		5th grade		8th grade	
Weight outcome	NSLP only	SBP and NSLP	NSLP only	SBP and NSLP	NSLP only	SBP and NSLP	NSLP only	SBP and NSLP
BMI *z*-score	0.119 (0.09)	−0.029 (0.09)	0.045 (0.10)	0.060 (0.10)	0.224 (0.15)	−0.004 (0.13)	−0.185 (0.14)	0.196 (0.13)
Overweight/ obese	0.111* (0.06)	−0.025 (0.05)	0.109 (0.07)	0.086 (0.06)	−0.044 (0.09)	−0.085 (0.08)	0.059 (0.09)	0.194** (0.08)
Normal weight	−0.103 (0.06)	0.031 (0.06)	−0.103 (0.08)	−0.072 (0.07)	0.130 (0.10)	0.093 (0.08)	−0.159 (0.10)	−0.197** (0.09)
N	640	840	430	590	320	310	250	250
	Midwest				West			
	5th grade		8th grade		5th grade		8th grade	
Weight outcome	NSLP only	SBP and NSLP	NSLP only	SBP and NSLP	NSLP only	SBP and NSLP	NSLP only	SBP and NSLP
BMI *z*-score	−0.053 (0.11)	0.090 (0.10)	−0.018 (0.11)	0.029 (0.10)	0.188 (0.16)	−0.052 (0.16)	−0.057 (0.14)	−0.061 (0.15)
Overweight/ obese	0.019 (0.06)	−0.002 (0.06)	0.011 (0.07)	0.096 (0.07)	0.085 (0.07)	0.053 (0.07)	0.019 (0.09)	0.063 (0.08)
Normal weight	0.003 (0.07)	0.000 (0.07)	−0.045 (0.07)	−0.072 (0.08)	−0.099 (0.09)	−0.025 (0.09)	−0.007 (0.10)	−0.026 (0.09)
N	480	550	440	470	400	450	320	360

*Indicates statistically significant at the 10% level.
**Indicates statistically significant at the 5% level.
Standard errors in parentheses.
BMI = body mass index.
NSLP = National School Lunch Program.
SBP = School Breakfast Program.
Results include the following covariates: gender, race, age, birth weight, past BMI, number of children enrolled at the school, whether the school is Title I, the percentage of children eligible for FRP meals, mother's education level, father's education level, whether the mother works full time, whether the parents are married, household income, urbanicity, number of breakfasts and dinners the family eats together, and whether the household is food insecure.
Unweighted sample sizes are rounded to the nearest 10 per IES policy.

Our results show both shorter- and longer-term program impacts across both subsets of students. The DID methodology examines students who only participate in the program(s) for certain years, which could be because of intermittent changes in household income; therefore, the results focus on shorter-term impacts. Using DID, we found impacts on child weight for low-income student participants (including those participating in only NSLP and those participating in both NSLP and SBP). In the subgroup analyses, these results are even more prominent in the South, Northeast, and rural areas. The DID results potentially indicate that no matter when the child enters into these programs, the nutritional value of the food is such that the child has a higher probability of gaining weight. Similarly, Li and Hooker (2010) found statistically significant effects on BMI for children eligible for free- and reduced-price NSLP and SBP. They found that children taking part in the NSLP or SBP have a higher probability of being overweight. These are similar to some of our results: for example, our ATT results found that children participating in both programs from 1st to 8th grade had a statistically significant higher probability of being overweight.

Our results do not support those of Bhattacharya et al. (2006) who found that children with access to SBP have a healthier diet when school is in session than when school is not in session because SBP improves the nutrient outcomes of the participants; however, the authors do not mention whether these children also participate in NSLP. Furthermore, Gleason and Dodd (2009) found no evidence of a relationship between NSLP participation and child BMI which is similar to some of our results. For example, we found no statistically significant relationship in our DID results for students switching NSLP status between 5th and 8th grade. We also found no relationship between NSLP participation and child BMI in our ATT results for students participating in only NSLP from 1st to 5th grade. Gleason and Dodd (2009) did find that SBP participation was associated with significantly lower BMI, particularly among non-Hispanic, white students which is a result we did not find; however, their paper did not distinguish between those students only participating in NSLP versus participating in both programs.

The ATT analysis focused on those students who live in households with persistent poverty. These results show the potential for longer-term impacts on child weight, particularly on those low-income students participating in both programs. These results support those of Schanzenbach (2008) who found that children who consume school lunches are more likely to be obese than those who bring their lunches even though they enter kindergarten with the same obesity rates. They also support those of Millimet et al. (2010) who found that NSLP participation exacerbates the current epidemic of childhood obesity. However, Millimet et al. (2010) also found strong evidence of nonrandom selection into SBP. Both of these studies took into account program selection bias in their analysis.

Another implication of the results is that the differences in the nutritional value of the food choices offered in middle school compared with elementary school may have an impact on child weight instead of length of participation in the programs. Overall, results suggest that the school meal programs do have a nontrival impact on child weight with the tendency toward overweight for students.

In terms of policy implications, with the Community Eligibility Provision having taken effect in the 2014–2015 school year across the nation, the need to continue to examine the impacts of these programs on child weight is even greater. Furthermore, with the release of the school nutrition standards in the Healthy, Hunger-Free Kids Act (HHFKA) of 2010, healthier school meals are required to be phased in over several years. These nutrition standards have the potential to help combat the childhood obesity epidemic because the legislation provides resources to increase the nutritional quality of food provided by USDA. The legislation also provides resources for schools and communities to utilize local farms and gardens to provide fresh produce as part of school meals. However, one key facet that needs to be considered is how children will respond to healthier meals and whether they will consume the food. This problem can partially be overcome by continuing and expanding initiatives such as the Chefs Move to Schools and Small Farms/School Meals Initiative. These programs support SBP and NSLP while encouraging students to eat healthier by having them take more of an interest in where food comes from and how it is prepared. This research is not set up to study the effects of HHFKA because the kindergarten cohort of the ECLS-K data began in the 1998–1999 school year finishing in 2006–2007, while the HHFKA was signed into law in 2010.[17] However, our findings are still useful because

[17]It should be noted that the 8th grade data was not made publicly available until 2010.

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they shed light on the magnitude of needs for nutrition improvement for the school meal programs before HHFKA, and the heterogeneous results in our subset analyses can inform strategies for region-targeted program improvement even after HHFKA is full in effect. Furthermore, our paper provides additional theoretical and empirical methods in this area of research that can be used for later evaluation of HHFKA once data is available.

It is also important to investigate whether the impacts of these school meal programs extend beyond effects on child BMI. For instance, some research has shown links between nutrition, school meal program participation, and academic performance (Averett and Stifel, 2010; Belot and James, 2011; Glewwe *et al*., 2001). To our knowledge, no research examines the impacts of NSLP on student achievement; however, if these programs can be linked to children's academic achievement, stronger evidence will be available to support the programs' effectiveness.

CONFLICT OF INTEREST

None.

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