School Nutrition Programs and the Incidence of Childhood Obesity

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Abstract
In light of the recent rise in childhood obesity, the School Breakfast Program (SBP) and National School Lunch Program (NSLP) have received renewed attention. Using panel data on over 13,500 primary school students, we assess the relationship between SBP and NSLP participation and (relatively) long-run measures of child weight. After documenting a positive association between SBP participation and child weight, and no association between NSLP participation and child weight, we present evidence indicating positive selection into the SBP. Allowing for even modest positive selection is sufficient to alter the results, indicating that the SBP is a valuable tool in the current battle against childhood obesity, whereas the NSLP exacerbates the current epidemic.

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1 Introduction

As is quite evident from recent media reports, childhood obesity is deemed to have reached epidemic status. Data from the National Health and Nutrition Examination Survey (NHANES) I (1971–1974) and NHANES 2003–2004 indicate that the prevalence of overweight preschool-aged children, aged 2-5 years, increased from 5.0% to 13.9% over this time period.[1] Among school-aged children, the prevalence has risen from 4.0% to 18.8% for those aged 6-11; 6.1% to 17.4% for those aged 12-19 years.[2]

Given this backdrop, policymakers in the US have acted in a number of different directions, particularly within schools. Public Law 108-265 required schools to have a local wellness program by the beginning of the 2006-2007 school year, which must address both nutritional and physical activity goals. The CDC has started the KidsWalk-to-School Program to encourage communities to partner with parents and local public safety officials to enable students to safely walk or bicycle to school in groups accompanied by adults. Some schools have banned soda machines and vending machines containing unhealthy snacks, while others have taken aggressive measures to ensure the provision of nutritious meals.[3] Texas reinstated a physical education requirement, which had been previously removed in favor of more academic pursuits (Schanzenbach 2007). In November 2007, the US Department of Health and Human Services (HHS) launched the Childhood Overweight and Obesity Prevention Initiative.

Aside from these recent policy developments, two federal programs that have long been in existence have been met with renewed interest: the School Breakfast Program (SBP) and the National School Lunch Program (NSLP). Given the number of children affected and *potentially* affected by these programs, combined with the fact that the infrastructure for these programs is already in existence, it is the relationship between the SBP, NSLP, and child health that we analyze here. Specifically, we have three main objectives. First, assess the relatively long-run relationship between participation in school nutrition programs and child weight using data collected after the most recent, large-scale reforms of the programs. Second, analyze the process by which children select into the SBP and NSLP. Finally, assess the impact of such selection on our ability to infer a causal relationship.

Understanding the relationship between school nutrition programs and child weight is clearly important. As the incidence of overweight children has increased, so too has our understanding of the negative consequences that result. First and foremost, overweight children are significantly more likely to become obese adults. Serdula et al. (1993) find that one-third of overweight preschool-aged children and one-half of

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[1] Overweight is defined as an age- and gender-specific body mass index (BMI) greater than the 95^{th} percentile based on growth charts from the Center for Disease Control (CDC).

[2] See http://www.cdc.gov/nccdphp/dnpa/obesity/childhood/prevalence.htm.

[3] Andersen and Butcher (2006) find that the elasticity of BMI with respect to junk food exposure in schools is roughly 0.1.

overweight school-aged children become obese adults. Second, the adverse health effects of obesity include, among others, depression, sleep disorders, asthma, cardiovascular and pulmonary complications, and type II diabetes (Ebbling et al. 2002). In terms of economic costs, Finkelstein et al. (2003) report that medical spending attributed to obesity was close to $80 billion, or 9% of total medical expenditures, in the US in 1998. Bleich et al. (2007) provide a recent overview of the costs and consequences of adult obesity.

In this study, we utilize panel data on over 13,500 children during early primary school to examine the relatively *long-run* effect of participation in *both* the SBP and NSLP. Specifically, we analyze the relationship between child weight in the spring of third grade and program participation in spring of kindergarten. Analyzing the long-run impact allows us to capture dynamic effects of program participation such as nutritional habit formation and resource reallocation within households. In addition, after assessing the nature of selection into both programs, we examine the sensitivity of the estimated program effects to non-random selection, borrowing several methods from the program evaluation literature.

Our results are striking, yielding three salient findings. First, while SBP participation in kindergarten is *associated* with greater child weight in third grade and a greater change in child weight between kindergarten and third grade for many children, NSLP participation and child weight are *unrelated*. However, we find strong evidence of non-random selection into the SBP; children who gained more weight prior to kindergarten are more likely to participate. Consonant with Schanzenbach (2007), selection bias does not seem to be a concern when analyzing the NSLP. Finally, in nearly all cases, the positive associations between SBP participation and child weight are found to be extremely sensitive to non-random selection; even a *modest* amount of positive selection is sufficient to eliminate, if not reverse, the initial results for SBP. Moreover, allowing for modest positive selection into the SBP leads to a *detrimental* effect of NSLP participation on child weight; ignoring non-random selection into SBP biases the impact of the NSLP toward zero. Thus, admitting even modest positive selection into the SBP implies that the SBP is a *valuable* tool in the current battle against childhood obesity, whereas the NSLP *exacerbates* the current epidemic. The beneficial effect of the SBP, and the deleterious impact of the NSLP, strengthen the findings in Bhattacharya et al. (2006) and Schanzenbach (2007), respectively.

The remainder of the paper is organized as follows. Section 2 provides background information, both on the school nutrition programs themselves, as well as the previous literature. Section 3 presents a simple theoretical framework for thinking about school nutrition programs. Section 4 describes the empirical methodology and the data. Section 5 presents the results, while Section 6 concludes.

2 Background

2.1 Institutional Details

The NSLP was developed gradually, and made permanent by the National School Lunch Act in 1946. The program provides lunch to over 29 million children each school day, covering approximately 99,000 schools (95% of all public and private schools), with 17.5 million students receiving reduced price or free meals.[4] The SBP was established in 1966 by the Child Nutrition Act, and made permanent by subsequent amendments in 1975. During the 2005-2006 school year, the SBP provided breakfast to roughly 9.6 million children in 82,000 schools, with 7.7 million children receiving reduced price or free breakfasts (Cooper and Levin 2006).

As evidenced by these figures, the SBP is under-utilized relative to the NSLP. Roughly 83% of schools participating in the NSLP also participated in the SBP during the 2005-2006 school year, and roughly 45 students qualifying for free or reduced price meals participated in the SBP for every 100 students participating in the NSLP (Cooper and Levin 2006). That said, SBP participation is on the rise, having increased in all but three states from the 2004-2005 school year to the 2005-2006 school year.

The SBP and NSLP are organized in a similar fashion. Both programs are federally funded. Each program is overseen by the Food and Nutrition Service (FNS) of the US Department of Agriculture (USDA), but administered by state education agencies. Schools deciding to participate in the programs must offer meals that meet federal nutritional requirements. In addition, students residing in households with family incomes at or below 130% of the federal poverty line are eligible for free meals, while those in households with family incomes between 130% and 185% of the federal poverty line are entitled to reduced price meals.[5] Eligible children apply directly to the school, with the same application covering both the SBP and NSLP. In addition, children from households that receive aid through food stamps, Temporary Assistance for Needy Families, or the Food Distribution Program on Indian Reservations are automatically eligible for free meals. All other students pay full price, though meals are still subsidized by the federal government to a limited extent.

Schools establish their own prices for full price meals, but prices for reduced price meals are capped. Schools have flexibility with respect to the specific foods served, but are constrained by the fact they must operate their meal services as non-profit programs. In the 2005 fiscal year, the NSLP cost the federal government roughly $7 billion, while federal expenditures on the SBP in fiscal year 2006 totalled $2 billion.[6]

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[4] See http://www.fns.usda.gov/cnd/lunch/AboutLunch/NSLPFactSheet.pdf.

[5] For the period July 1, 2007, through June 30, 2008, 130% (185%) of the federal poverty line for a family of four is $26,845 ($38,203). The maximum price allowed for breakfast (lunch) to students qualifying for reduced price is $0.30 ($0.40).

[6] See http://www.frac.org/pdf/cnnslp.PDF and http://www.frac.org/pdf/cnsbp.PDF.

As stated above, reimbursement is conditional on the meals meeting federal nutritional requirements, established by Congress in 1995 under the "School Meals Initiative for Healthy Children" (SMI). SMI represented the largest reform of the programs since their inception (Lutz et al. 1999). For breakfast, this entails no more than 30% of the meal's calories be derived from fat, and less than 10% from saturated fat. Breakfasts also must provide one-fourth of the Recommended Dietary Allowance (RDA) for protein, calcium, iron, Vitamin A, Vitamin C, and contain an age-appropriate level of calories. For lunches, the same restrictions on fat apply. However, lunches must provide one-third of the RDA for protein, calcium, iron, Vitamin A, Vitamin C, and an age-appropriate level of calories calories. In addition, all meals are recommended to reduce levels of sodium and cholesterol, as well as increase the level of dietary fiber.

Enforcement of the SMI requirements is handled by requiring states to monitor local school food authorities by conducting reviews at least once every five years. In turn, the FNS monitors state compliance with this review requirement. The FNS has also begun to provide regional and local training to ensure adequate overview.

2.2 Literature Review

Given the size and cost of these programs, each has been studied to some extent over the decades. In the early 1990s, a series of studies were conducted utilizing the 1992 School Nutrition Dietary Assessment (SNDA-1) study. As part of the study, a random sample of school meals were analyzed, in addition to the diets of children. Gleason (1995) finds that SBP availability is not associated with a higher probability of eating breakfast. Moreover, the author finds that lunches provided under the NSLP derived an average of 38% of food energy from fat, exceeding guidelines. Burghardt et al. (1995) report that meals provided under the NSLP exceeded guidelines for total and saturated fat and sodium, whereas meals provided under the SBP exceeded guidelines for saturated fat and cholesterol. Gordon et al. (1995) use 24-hour dietary recall data and conclude that both SBP and NSLP participation are associated with higher intake of fat and saturated fat, but also some nutrients.

The results of the analyses using the SNDA-1 led to the 1995 SMI discussed above. While the SMI required schools to follow the nutrition guidelines by the 1996-1997 school year, some schools received a waiver until the 1998-1999 school year (Lutz et al. 1999). A second study, the SNDA-2, was conducted in 1998-1999. The evidence suggests some effect of the SMI on the nutritional content of meals, but school lunches in particular still have much room for improvement (Schanzenbach 2007).[7]

Since the SNDA-1 study, more recent analyses have focused greater attention on identifying the *causal* impact of SBP or NSLP participation on child health. Gleason and Suitor (2003) use two nonconsecutive

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[7] See also http://www.iom.edu/Object.File/Master/31/064/Jay%20Hirschman.IOM%20Presentation.Oct%2026%202005.pdf.

days of 24-hour dietary recall data to obtain fixed effects estimates of NSLP participation. The authors find positive effects on nutrient intakes, but also on dietary fat. Hofferth and Curtin (2005) use data from the 1997 Child Development Supplement of the Panel Study for Income Dynamics (PSID) and find no effect of SBP participation on the probability of being overweight after controlling for NSLP participation. In addition, instrumental variables estimates – using public school attendance as the exclusion restriction – indicate no impact of NSLP participation. Bhattacharya et al. (2006) analyze the effects of SBP availability in the school on nutritional intake using NHANES III, which spans 1988-1994 (thus pre-dating the SMI). The authors employ a difference-in-differences strategy (comparing in-school versus out-of-school periods in schools participating and not participating in the SBP), concluding that SBP availability "has no effect on the total number of calories consumed or on the probability that a child eats breakfast, but it improves the nutritional quality of the diet substantially" (p. 447). Schanzenbach (2007) utilizes panel data methods, as well as a regression discontinuity (RD) approach that exploits the sharp income cut-off for eligibility for reduced-price meals, to assess the impact of the NSLP. She finds that NSLP participation increases the probability of being obese due to the additional calories provided by school lunches. However, she finds little substantive difference between the RD estimates and those based on a panel data approach, suggesting little selection into the NSLP on the basis of unobservables that vary over time and across schools.

Finally, a few studies offer less direct evidence of the possible effects of the SBP and NSLP. For instance, Long (1991) assesses the crowding-out impact of SBP and NSLP benefits on total household food expenditures. The author finds that one dollar of NSLP (SBP) benefits displaces only $0.60 (none) of household food expenditures. Thus, both programs increase the *total value* of food consumed by the household. von Hippel et al. (2007) show that children are more at-risk of gaining weight during summer vacation than during the school-year. While this is potentially attributable to children's propensity to consume more food while at home, it could also be explained by the lack of access to school meal programs during the summer for non-summer school attendees.

We add to this literature in three important ways. First, we assess the *long-run* relationship between participation in *both* the SBP and NSLP program and children's weight after the reforms enacted under the SMI should have been fully implemented. Most prior research (to our knowledge) assesses the contemporaneous relationship between SBP and/or NSLP participation and children's weight, typically focuses on only one of the programs (not both), and uses data from before the changes instituted under the SMI have been fully implemented. Second, we assess the nature of selection into both programs using data on birthweight and weight at the time of entry into kindergarten. Finally, we examine the sensitivity of the estimated program effects to non-random selection.

3 Theoretical Motivation

To provide some context for the empirical analysis, it is useful to think about the intrahousehold resource allocation effects of the SBP and NSLP. Figure 1 illustrates a very simple model. Households maximize utility, $U(c, f)$, where c is non-food consumption and f is food consumption subject to a standard budget constraint (as well as an implicit biological constraint restricting food consumption from falling below some threshold). In the figure, the solid budget constraint represents the initial budget constraint without school-provided nutrition programs. The corresponding optimal consumption bundle is labelled as point A. The dashed budget constraint incorporates the SBP and NSLP assuming children in the household receive an infra-marginal transfer of food for free at school. Thus, the programs lead to a kinked budget constraint, where the kink point lies to the left of point A given the assumption of an infra-marginal transfer (whereby the size of the transfer is less than food consumption without the program).

With an infra-marginal transfer, it is well known that the impact of the transfer is equivalent to pure income transfer in that the result is a parallel shift out of the budget constraint near the original consumption bundle, point A. Since the transfer has only an income effect, the household will respond by increasing consumption of both c and f if both are normal goods. Point B illustrates this possible outcome. However, if the income elasticity of food consumption is zero, then the household may instead move to point C, in which case the household utilizes the savings from the transfer program purely to finance an increase in non-food consumption. This latter possibility is consistent with the findings in Bhattacharya et al. (2006) with respect to the SBP (as participation does not alter total caloric intake), but the former is consonant with the earlier findings in Long (1991) for both programs and Schanzenbach (2007) with respect to the NSLP.[8]

This model, while quite simple, illustrates two key points. First, participation in the SBP and NSLP may or may not increase food consumption. In the event that food consumption does increase, any health benefits of the SBP and NSLP require the nutritional gains from the food provided under these programs to more than compensate for the increase in overall food consumption if child health is to be improved. Second, participation in the SBP and NSLP provides an income benefit to households that allows households to increase their non-food consumption. Such an increase in consumption has theoretically ambiguous health consequences. For example, if the household uses the additional resources to buy a video game machine or to fund an extracurricular activity. Thus, in the end, the role of the SBP and NSLP in the childhood obesity epidemic – positive or negative – is an empirical question.

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[8] Note, the distinction between the results in Bhattacharya et al. (2006) and Schanzenbach (2007) should not be interpreted as conflicting results across the two studies as the former (latter) focuses on the SBP (NSLP).

4 Empirics

4.1 Methodology

To assess the impact of school nutrition programs on child health, we utilize several estimators. To contrast the estimators in terms of the identification assumptions required, we utilize the potential outcomes framework often adopted in the program evaluation literature. However, here, we are simultaneously considering two treatments: SBP and NSLP participation.

To begin, let y_{1i} and y_{2i} denote child health if the child participates in the SBP only (denoted as $\widetilde{D}_{1i} = 1$) and NSLP only (denoted as $\widetilde{D}_{2i} = 1$), respectively. Let y_{3i} denote child health if the child participates in both programs (given by $\widetilde{D}_{3i} = 1$), and y_{0i} denote child health in the absence of either treatment (corresponding to $\widetilde{D}_{1i} = \widetilde{D}_{2i} = \widetilde{D}_{3i} = 0$). In this set-up, the effect of participating in the SBP only relative to the control of no participation in either program on the health of child i is given by $\tau_{1i} \equiv y_{1i} - y_{0i}$. Similarly, $\tau_{2i} \equiv y_{2i} - y_{0i}$ and $\tau_{3i} \equiv y_{3i} - y_{0i}$ measure the effect on the health of child i of participating in the NSLP only and of participating in both programs, respectively, relative to the control of no participation in either program. However, given the usual missing counterfactual problem, only $y_i = \widetilde{D}_{1i}y_{1i} + \widetilde{D}_{2i}y_{2i} + \widetilde{D}_{3i}y_{3i} + (1 - \widetilde{D}_{1i})(1 - \widetilde{D}_{2i})(1 - \widetilde{D}_{3i})y_{0i}$ is observable.

To proceed, we specify a structural relationship for each potential outcome. Define

$$\begin{aligned} y_{0i} &= \mu_0(x_i) + u_{0i} \\ y_{1i} &= \mu_1(x_i) + u_{1i} \\ y_{2i} &= \mu_2(x_i) + u_{2i} \\ y_{3i} &= \mu_3(x_i) + u_{3i} \end{aligned} \tag{1}$$

where $\mathrm{E}[y_d|x_i] = \mu_d(x_i)$, $d = 0, 1, 2, 3$, and x_i is a vector of observable attributes of child i (including an intercept). u_d captures the impact of unobservable attributes on child health when $D = d$, $d = 0, 1, 2, 3$.

Assuming $\mu_d(x_i) = x_i\beta_d$, $d = 0, 1, 2, 3$, and $\beta_0 = \beta_1 = \beta_2 = \beta_3$ except for the intercept terms, then one obtains the following regression model

$$y_i = x_i\beta_0 + \tau_1\widetilde{D}_{1i} + \tau_2\widetilde{D}_{2i} + \tau_3\widetilde{D}_{3i} + \left[u_{0i} + \widetilde{D}_{1i}(u_{1i} - u_{0i}) + \widetilde{D}_{2i}(u_{2i} - u_{0i}) + \widetilde{D}_{3i}(u_{3i} - u_{0i})\right] \tag{2}$$

where τ_d, $d = 1, 2, 3$, is the constant treatment effect. Furthermore, if one assumes that the participation in both programs is additive, such that $\tau_3 = \tau_1 + \tau_2$ and $u_{3i} = u_{2i} + u_{1i} - u_{0i}$ for all i, then (2) simplifies to

$$y_i = x_i\beta_0 + \tau_1 D_{1i} + \tau_2 D_{2i} + [u_{0i} + D_{1i}(u_{1i} - u_{0i}) + D_{2i}(u_{2i} - u_{0i})] \tag{3}$$

where $D_{1i} = 1$ for all SBP participants (zero otherwise) and $D_{2i} = 1$ for all NSLP participants (zero otherwise).[9] In other words, $D_{1i} = 1$ if $\widetilde{D}_{1i} = 1$ or $\widetilde{D}_{3i} = 1$, and $D_{2i} = 1$ if $\widetilde{D}_{2i} = 1$ or $\widetilde{D}_{3i} = 1$.

For OLS estimation of (3) to yield a consistent estimate of τ_1 and τ_2, participation in the SBP and NSLP must be independent, conditional on x, of unobservables that impact child health without participating, u_0, and unobserved, child-specific gains from participation in either program, $u_1 - u_0$ and $u_2 - u_0$.

In contrast, a consistent estimate of τ_1 and τ_2 may be obtained under two alternative sets of assumptions given the nature of the data (discussed below). First, given data prior to exposure to the SBP and NSLP, one may express child health in the pre-treatment period, $t-1$, and post-treatment period, t, by

$$\begin{aligned} y_{it} &= x_i\beta_{0t} + \tau_1 D_{1it} + \tau_2 D_{2it} + [u_{0it} + D_{1it}(u_{1it} - u_{0it}) + D_{2it}(u_{2it} - u_{0it})] && (4) \\ y_{i,t-1} &= x_i\beta_{0,t-1} + u_{0i,t-1} && (5) \end{aligned}$$

where the child attributes, x, are time invariant, but the effects of these attributes are allowed to vary over time. First-differencing yields the following estimating equation

$$\Delta y_i = x_i\Delta\beta_0 + \tau_1 D_{1i} + \tau_2 D_{2i} + [\Delta u_{0i} + D_{1i}(u_{1it} - u_{0it}) + D_{2i}(u_{2it} - u_{0it})]\,. \tag{6}$$

where Δ indicates the change from the pre-treatment period. OLS estimation of (6) yields a consistent estimate of τ_1 and τ_2 if participation in the SBP or NSLP is uncorrelated with *changes* over time in unobservables impacting child health under no participation in either program, Δu_0, in addition to the previous identification assumptions.

Second, given data on multiple students from the same school, (3) and (6) may each be augmented to include school fixed effects, following the strategy employed in Schanzenbach (2007). The benefit of including school fixed effects is that it accounts for potential non-random selection into schools based on the availability of school nutrition programs. This yields a consistent estimate of τ_1 and τ_2 if participation in the SBP or NSLP is uncorrelated with child-level deviations in u or Δu, as well as unobserved, child-specific gains from participation, from their respective school-level averages.

In addition to the preceding parametric estimators, we also estimate the average treatment effect (ATE) of each program using propensity score matching (PSM). Now quite commonplace in economics and other disciplines, it is well known that PSM estimation yields two potential benefits over regression methods (Smith and Todd 2005). First, it is a semi-parametric estimator in that one does not need to specify a

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[9] This turns out to be a necessary restriction as there is not sufficient variation in the data to seperately identify the effect of SBP participation in isolation, τ_1, from SBP participation in conjunction with NSLP participation, τ_3. Thus, in our empirical analysis, we are predominantly identifying the impact of SBP participation using variation in outcomes from children participating in both programs relative to children participating only in the NSLP.

functional form for potential outcomes; $\mu_d(x_i)$ is left unspecified for all d. Second, issues of common support are explicitly addressed. Specifically, we estimate the ATE using only those observations for which the estimated propensity score (i.e., the probability of receiving the treatment given x) lies in the intersection of the supports for the treatment and control groups. In contrast, regression estimators – by virtue of the fact that they utilize the entire sample – may extrapolate across observations with very different observable attributes. Aside from these two issues, PSM estimation relies on the same identification assumptions as detailed above.[10]

Finally, because all of the preceding estimators are susceptible to bias from selection on (at least some type of) unobservables, we borrow various strategies from the program evaluation literature to assess the sensitivity of our results to any remaining selection on unobservables. Specifically, for the parametric models, we apply the procedures developed in Altonji et al. (2005). For the PSM models, we assess the sensitivity of the results using Rosenbaum bounds (Rosenbaum 2002). We discuss these below.

4.2 Data

The data are obtained from *Early Childhood Longitudinal Study-Kindergarten Class of 1998-99* (ECLS-K). Collected by the US Department of Education, the ECLS-K follows a nationally representative cohort of children throughout the US from fall and spring kindergarten, fall and spring first grade, and spring third grade. The sample includes 17,565 children from 994 schools.

We measure participation in school nutrition programs at the earliest possible date, which is in spring kindergarten.[11] However, we measure the health status of each child either in spring third grade or as the change from fall kindergarten to spring third grade. Not only does the nature of the timing improve the likelihood that the assumptions required for consistent estimation are met, but it also implies that we are analyzing more of the long-run relationship between child health and participation in the two programs. The long-run impact may differ in magnitude from the contemporaneous effect due to the development of nutritional habits, leading to a cumulative effect. Alternatively, reallocation of resources within households in response to any change in child health that may result from program participation or due to the income effect of program participation may alter the direction and magnitude of the impact.[12]

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[10] To implement the PSM estimator, we use kernel weighting with the Epanechnikov kernel and fixed bandwidth of 0.10. Standard errors are obtained using 100 repetitions. We perform the analysis twice, once using SBP participation as the treatment (i.e., D_1) and once using NSLP participation as the treatment (i.e., D_2).

[11] The relevant questions were not asked in the fall kindergarten wave.

[12] The long-run effect we seek to estimate also reflects, at least to some extent, the short-run impact as well; the correlation coefficients for program participation in spring kindergarten and spring third grade are 0.51 and 0.29 for the SBP and NSLP, respectively.

To measure child health, we utilize data on the age (in months) and gender of each child, as well as data on the weight and height of each child. The data allow us to construct seven measures of child health: body mass index (BMI) in levels or logs, growth rate in BMI from fall kindergarten to spring third grade, BMI percentile, change in BMI percentile from fall kindergarten to spring third grade, and indicators for overweight and obesity status, where percentiles are determined based on age- and gender-specific growth charts.[13] For the sake of expositional convenience, we define overweight (obese) as a BMI above the 85^{th} (95^{th}) percentile.

To control for parental and environmental factors, the following covariates are included in x: child's race (white, black, Hispanic, Asian, and other) and gender, child's birthweight, household income, mother's employment status, mother's education, number of children's books at home, mother's age at first birth, an indicator if the child's mother received WIC benefits during pregnancy, region, city type (urban, suburban, or rural), and the amount of food in the household. Finally, we also include higher order and interaction terms involving the continuous variables, as well as fall kindergarten measures of child health.[14]

Given the nature of our data, children with missing data for gender and race are dropped from our sample. Missing values for the remaining control variables are imputed and imputation dummies are added to the control set. However, particular care was needed to clean the data on child age, height, and weight. In terms of age, children with missing values in all waves are dropped, while missing ages in particular waves are imputed assuming all fall and all spring interviews were conducted during the same month each wave, and that spring interviews were conducted six months after fall interviews of the same school year. For height, we drop students with missing height in at least three waves, students with missing height in two waves but whose reported height falls at least once over time, and students whose reported height falls at least twice over time. For the remainder of students, we impute missing height or values of height that represented a decline from previously reported height by regressing 'valid' measures of height on age and imputing height. If the imputed value of height still represents a decline in height from previously reported height, the student is dropped. For weight, we begin by identifying suspicious values; those representing large declines or large gains in weight from the previous wave. Then, we drop students with missing weight in at least three waves, students with missing weight in two waves but whose reported weight falls by more than 15 pounds across two waves, and students with missing weight in at least one wave and a suspicious value in at least one other wave. For the remainder of students, we impute missing weight or suspicious values of weight by regressing 'valid' measures of weight on age and imputing weight. If the imputed value

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[13] Percentiles are obtained using the -*zanthro*- command in Stata, which computes the age- and gender-specific percentiles based on pre-epidemic distributions summarized in the 2000 CDC growth charts.

[14] Except for maternal employment, all controls come from either the fall or spring kindergarten survey.

Table A1. Summary Statistics

	Full Sample		Particpation in Neither		SBP Only		NSLP Only		Participation in Both	
Variable	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**	**Mean**	**SD**
SBP Participation (1 = Yes)	0.234	0.423	0	0	1	0	0	0	1	0
NSLP Participation (1 = Yes)	0.575	0.494	0	0	0	0	1	0	1	0
Third Grade Child Weight										
BMI	18.404	3.861	18.124	3.536	19.155	4.537	18.358	3.873	18.933	4.266
BMI Growth Rate	0.112	0.126	0.104	0.119	0.130	0.132	0.110	0.125	0.128	0.137
BMI percentile	62.326	30.105	60.966	29.867	65.363	30.300	61.686	30.409	65.697	29.739
Change in BMI Percentile	1.295	22.887	0.589	22.473	3.471	23.587	1.048	23.148	2.826	23.054
Overweight (1 = Yes)	0.325	0.468	0.304	0.460	0.397	0.490	0.320	0.466	0.365	0.481
Obese (1 = Yes)	0.171	0.377	0.150	0.357	0.248	0.432	0.172	0.377	0.204	0.403
Fall Kindergarten Child Weight										
BMI	16.265	2.142	16.168	1.977	16.600	2.667	16.259	2.179	16.423	2.295
BMI percentile	61.030	28.452	60.376	28.122	61.892	30.077	60.638	28.840	62.871	28.133
Overweight (1 = Yes)	0.258	0.438	0.244	0.430	0.293	0.456	0.258	0.437	0.282	0.450
Obese (1 = Yes)	0.114	0.318	0.103	0.304	0.185	0.389	0.114	0.318	0.125	0.331
Age (in months)	110.767	4.356	110.725	4.347	110.936	4.087	110.749	4.345	110.861	4.424
Gender (1 = boy)	0.507	0.500	0.511	0.500	0.522	0.500	0.494	0.500	0.523	0.500
White (1 = Yes)	0.579	0.494	0.721	0.449	0.591	0.492	0.587	0.492	0.291	0.454
Black (1 = Yes)	0.138	0.345	0.050	0.218	0.122	0.328	0.123	0.328	0.334	0.472
Hispanic (1 = Yes)	0.174	0.379	0.125	0.330	0.185	0.389	0.186	0.390	0.246	0.431
Asian (1 = Yes)	0.054	0.226	0.058	0.235	0.045	0.207	0.056	0.231	0.041	0.199
Child's Birthweight (ounces)	118.284	20.040	120.015	19.510	117.542	21.788	117.970	19.495	115.600	21.407
Child's Birthweight (1 = Missing)	0.121	0.326	0.098	0.297	0.143	0.351	0.117	0.322	0.167	0.373
Central City (1 = Yes)	0.395	0.489	0.356	0.479	0.310	0.463	0.425	0.494	0.428	0.495
Urban Fringe & Large Town (1 = Yes)	0.377	0.485	0.475	0.499	0.340	0.475	0.346	0.476	0.250	0.433
Northeast (1 = Yes)	0.182	0.386	0.265	0.441	0.334	0.472	0.134	0.340	0.089	0.285
Midwest (1 = Yes)	0.250	0.433	0.293	0.455	0.236	0.425	0.239	0.427	0.189	0.391
South (1 = Yes)	0.346	0.476	0.192	0.394	0.278	0.448	0.413	0.492	0.535	0.499
Mother's Age at First Birth ≤ 19 Years Old (1 = Yes)	0.227	0.419	0.141	0.348	0.290	0.454	0.208	0.406	0.418	0.493
Mother's Age at First Birth is 20-29 Years Old (1 = Yes)	0.522	0.500	0.566	0.496	0.507	0.501	0.544	0.498	0.398	0.490
Mother's Age at First Birth (1 = Missing)	0.104	0.305	0.085	0.279	0.143	0.351	0.102	0.303	0.139	0.346
WIC Benefits During Pregnancy (1 = Yes)	0.339	0.473	0.189	0.391	0.504	0.501	0.323	0.468	0.634	0.482
WIC Benefits During Pregnancy (1 = Missing)	0.112	0.315	0.095	0.293	0.134	0.342	0.113	0.316	0.141	0.348
Mother's Education = High School (1 = Yes)	0.198	0.398	0.172	0.377	0.278	0.448	0.197	0.398	0.239	0.426
Mother's Education = Some College(1 = Yes)	0.281	0.450	0.304	0.460	0.301	0.460	0.292	0.455	0.218	0.413
Mother's Education = Bachelor's Degree (1 = Yes)	0.144	0.351	0.198	0.398	0.057	0.232	0.152	0.359	0.038	0.192
Mother's Education = Advanced College Degree (1 = Yes)	0.084	0.277	0.125	0.330	0.027	0.162	0.078	0.268	0.023	0.151
Mother's Education (1 = Missing)	0.209	0.407	0.168	0.374	0.221	0.415	0.206	0.405	0.293	0.455

Notes: N = 13,534 (full sample); 5,423 (participation in neither); 335 (SBP only); 4,950 (NSLP only); 2,826 (SBP and NSLP). Data are from from the kindergarten wave of ECLS-K unless otherwise noted. Change in BMI percentile and BMI growth rate calculated using baseline data from fall kindergarten. Omitted category for race is 'other', city type is 'small town & rural', mother's age at first birth is greater than 29 years old, mother's employment is 'missing', mother's education is 'less than high school', and sufficient food is 'sometimes or often there is not enough to eat'.

Table A1 (cont.). Summary Statistics

Variable	Full Sample		Particpation in Neither		SBP Only		NSLP Only		Participation in Both	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Household Income (dollars)	52150	32034	61774	33666	38744	23611	52855	31091	34036	21285
Mother Employed During 3rd Grade (1 = Yes)	0.572	0.495	0.613	0.487	0.513	0.501	0.594	0.491	0.462	0.499
Mother Employed During 3rd Grade (1 = No)	0.204	0.403	0.206	0.405	0.242	0.429	0.186	0.389	0.229	0.420
Sufficient Food of Type Desired in Household (1 = Yes)	0.847	0.360	0.901	0.299	0.758	0.429	0.859	0.348	0.733	0.442
Sufficient Food, but not of Type Desired in Household (1 = Yes)	0.138	0.345	0.093	0.290	0.209	0.407	0.130	0.337	0.231	0.422
Sufficient Food (1 = Missing)	0.001	0.028	0.000	0.014	0.000	0.000	0.001	0.032	0.002	0.042
Number of Children's Books in Household	74.930	57.030	91.101	58.567	67.774	56.005	74.002	54.846	46.369	45.065
Number of Children's Books in Household (1 = Missing)	0.097	0.296	0.085	0.279	0.134	0.342	0.097	0.296	0.117	0.321

Notes: N = 13,534 (full sample); 5,423 (participation in neither); 335 (SBP only); 4,950 (NSLP only); 2,826 (SBP and NSLP). Data are from from the kindergarten wave of ECLS-K unless otherwise noted. Change in BMI percentile and BMI growth rate calculated using baseline data from fall kindergarten. Omitted category for race is 'other', city type is 'small town & rural', mother's age at first birth is greater than 29 years old, mother's employment is 'missing', mother's education is 'less than high school', and sufficient food is 'sometimes or often there is not enough to eat'.

Table A2. Sensitivity Analysis: Bivariate Probit Results with Different Assumptions Concerning Correlation Among the Disturbances by Risk Type

	Correlation of the Disturbances					
	Specification (1)					
	ρ = 0	**ρ = 0.1**	**ρ = 0.2**	**ρ = 0.3**	**ρ = 0.4**	**ρ = 0.5**
I. Normal Weight Entering Kindergarten						
A. Probability of Being Overweight						
School	0.124*	-0.043	-0.210*	-0.377*	-0.543*	-0.709*
Breakfast	(0.042)	(0.042)	(0.042)	(0.041)	(0.040)	(0.038)
School	-0.011	0.016	0.046	0.078†	0.112*	0.149*
Lunch	(0.035)	(0.035)	(0.035)	(0.035)	(0.034)	(0.034)
B. Probability of Being Obese						
School	0.155†	-0.013	-0.180*	-0.348*	-0.516*	-0.686*
Breakfast	(0.061)	(0.060)	(0.059)	(0.058)	(0.057)	(0.055)
School	0.008	0.037	0.070	0.107†	0.147*	0.192*
Lunch	(0.053)	(0.053)	(0.052)	(0.052)	(0.051)	(0.050)
II. Obese or Overweight Entering Kindergarten						
A. Probability of Being Overweight						
School	-0.046	-0.213*	-0.381*	-0.548*	-0.717*	-0.887*
Breakfast	(0.065)	(0.065)	(0.065)	(0.064)	(0.063)	(0.061)
School	-0.016	0.013	0.040	0.066	0.090	0.113†
Lunch	(0.057)	(0.057)	(0.057)	(0.056)	(0.056)	(0.056)
B. Probability of Being Obese						
School	0.032	-0.135†	-0.301*	-0.468*	-0.633*	-0.798*
Breakfast	(0.058)	(0.058)	(0.057)	(0.057)	(0.055)	(0.053)
School	0.027	0.056	0.086‡	0.115†	0.145*	0.174*
Lunch	(0.050)	(0.050)	(0.050)	(0.050)	(0.050)	(0.049)

NOTES: ‡ p<0.10, † p<0.05, * p<0.01. Standard errors in parentheses. Specification (1) refers to control set used in Column (1) in Table 1.
See Tables 1, 4, and text for details.

Table A3. Sensitivity Analysis: Amount of Selection on Unobservables Relative to Selection on Observables Required to Attribute the Entire SBP Effect to Selection Bias by Risk Type

	Specification (1)			Specification (2)		
	Cov(ε,ν)÷ Var(ν)	τ_1	Implied Ratio	Cov(ε,ν)÷ Var(ν)	τ_1	Implied Ratio
I. Normal Weight Entering Kindergarten						
BMI: Levels	8.825	0.305 (0.067)	0.035	1.002	0.243 (0.059)	0.242
BMI: Logs	0.437	0.017 (0.004)	0.038	0.051	0.013 (0.003)	0.261
BMI: Growth Rates	0.363	0.013 (0.003)	0.035	0.204	0.013 (0.003)	0.065
Percentile BMI: Levels	76.532	3.077 (0.798)	0.040	7.903	2.198 (0.668)	0.278
Percentile BMI: Changes	68.900	1.608 (0.716)	0.023	11.741	2.195 (0.668)	0.187
Probability of Being Overweight	4.561	0.033 (0.011)	0.007			
Probability of Being Obese	2.633	0.016 (0.006)	0.006			
II. Obese or Overweight Entering Kindergarten						
BMI: Levels	14.461	0.272 (0.189)	0.019	0.837	0.177 (0.131)	0.211
BMI: Logs	0.561	0.010 (0.008)	0.017	0.037	0.006 (0.006)	0.170
BMI: Growth Rates	0.396	0.006 (0.006)	0.015	0.225	0.006 (0.006)	0.028
Percentile BMI: Levels	20.935	-0.081 (0.620)	-0.004	3.058	-0.179 (0.557)	-0.058
Percentile BMI: Changes	10.621	-0.147 (0.559)	-0.014	7.906	-0.179 (0.557)	-0.023
Probability of Being Overweight	0.640	-0.013 (0.019)	-0.021	0.640	-0.013 (0.019)	-0.021
Probability of Being Obese	2.531	0.012 (0.023)	0.005	0.395	0.007 (0.020)	0.017

NOTES: Standard errors in parentheses. Specifications (1) and (2) refer to control sets used in Table 1. See Tables 1 and 5 for details.

Table A4. Propensity Score Matching Sensitivity Analysis by Risk Type: Rosenbaum Bounds (SBP)

	Γ = 1	**Γ = 1.2**	**Γ = 1.4**	**Γ = 1.6**	**Γ = 1.8**	**Γ = 2**	**Γ = 2.5**	**Γ = 3**
I. Full Sample								
BMI: Levels	p = 0.000	p = 0.000	p = 0.411	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000
BMI: Logs	p = 0.000	p = 0.000	p = 0.996	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000
BMI: Growth Rates	p = 0.000	p = 0.000	p = 0.873	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000
Percentile BMI: Levels	p = 0.000	p = 0.989	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000
Percentile BMI: Changes	p = 0.000	p = 0.000	p = 0.718	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000
Prob. of Being Overweight	p = 0.071	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000
Prob. of Being Obese	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.828	p = 1.000	p = 1.000	p = 1.000
II. Normal Weight Entering Kindergarten								
BMI: Levels	p = 0.000	p = 0.000	p = 0.069	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000
BMI: Logs	p = 0.000	p = 0.000	p = 0.840	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000
BMI: Growth Rates	p = 0.000	p = 0.000	p = 0.000	p = 0.985	p = 1.000	p = 1.000	p = 1.000	p = 1.000
Percentile BMI: Levels	p = 0.000	p = 0.487	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000
Percentile BMI: Changes	p = 0.000	p = 0.000	p = 0.610	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000
Prob. of Being Overweight	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.064	p = 1.000	p = 1.000
Prob. of Being Obese	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000
III. Obese or Overweight Entering Kindergarten								
BMI: Levels	p = 0.000	p = 0.000	p = 0.491	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000
BMI: Logs	p = 0.000	p = 0.002	p = 0.826	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000
BMI: Growth Rates	p = 0.000	p = 0.335	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000
Percentile BMI: Levels	p = 0.966	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000
Percentile BMI: Changes	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000
Prob. of Being Overweight	p = 0.527	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000	p = 1.000
Prob. of Being Obese	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.000	p = 0.191	p = 1.000	p = 1.000

NOTES: Rosenbaum critical p-values for test of the null of zero average treatment effect. For controls included in the propensty score, see Table 1.

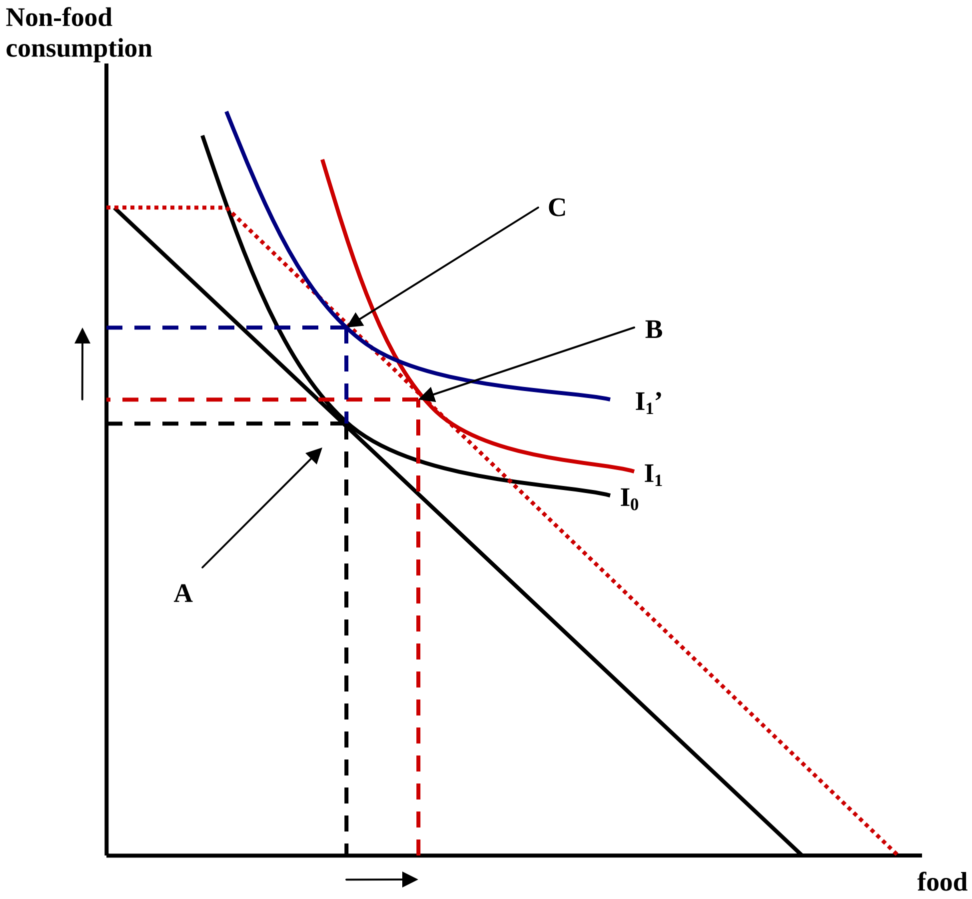

Figure 1. Theoretical Impact of Infra-Marginal Food Transfer Programs on Food and Non-Food Consumption.

NOTES: A – initial consumption point prior to food transfer program. B – final consumption point with food transfer program assuming food and non-food consumption are normal goods. C – final consumption point with food transfer program assuming non-food consumption is a normal good and the income elasticity of food consumption is zero.

Table 1. Full Sample Results

	OLS/Probit		School Fixed Effects	Propensity Score Matching
	(1)	(2)	(3)	(4)
I. BMI: Levels				
School	0.290*	0.209*	0.209*	0.353*
Breakfast	(0.092)	(0.056)	(0.063)	(0.120)
School	0.040	-0.004	-0.018	-0.022
Lunch	(0.075)	(0.046)	(0.062)	(0.096)
II. BMI: Logs				
School	0.014*	0.010*	0.010*	0.017*
Breakfast	(0.005)	(0.003)	(0.003)	(0.007)
School	0.002	-0.001	-0.002	-0.001
Lunch	(0.004)	(0.002)	(0.003)	(0.005)
III. BMI: Growth Rates				
School	0.010*	0.010*	0.010*	0.014*
Breakfast	(0.003)	(0.003)	(0.003)	(0.004)
School	0.000	-0.001	-0.002	0.000
Lunch	(0.002)	(0.002)	(0.003)	(0.003)
IV. Percentile BMI: Levels				
School	2.114*	1.478*	1.459†	2.178*
Breakfast	(0.714)	(0.510)	(0.575)	(1.023)
School	0.187	-0.258	-0.633	-0.023
Lunch	(0.582)	(0.415)	(0.560)	(0.729)
V. Percentile BMI: Changes				
School	1.009‡	1.475*	1.456†	2.462*
Breakfast	(0.548)	(0.510)	(0.575)	(0.826)
School	-0.350	-0.257	-0.633	-0.151
Lunch	(0.447)	(0.415)	(0.560)	(0.596)
VI. Probability of Being Overweight				
School	0.050	0.070†	0.017	0.031†
Breakfast	(0.032)	(0.036)	(0.011)	(0.016)
School	-0.004	-0.013	-0.007	-0.005
Lunch	(0.026)	(0.030)	(0.010)	(0.012)
VII. Probability of Being Obese				
School	0.055	0.064	0.017†	0.036*
Breakfast	(0.035)	(0.041)	(0.008)	(0.013)
School	0.015	0.032	0.001	-0.002
Lunch	(0.030)	(0.035)	(0.008)	(0.009)

NOTES: ‡ p<0.10, † p<0.05, * p<0.01. Standard errors in parentheses. Marginal effects reported in Panels VI and VII. Additional controls in each model: (1) age, gender dummy, child's birthweight, 4 race dummies, 2 city type dummies, 3 region dummies, 3 dummies for mother's age at first birth, dummies for whether mother received WIC benefits during pregancy, 5 mother's education dummies, 2 dummies for mother's current employment status, household income, number of children's books in the household, 3 dummies for the amount of food in the household, quadratic and cubic terms of all continuous variables, and the complete set of pairwise interactions among the continuous variables. (2) previous control set plus the lagged dependent variable (from the fall kindergarten wave), quadratic and cubic terms of the lagged dependent variable (Panels I -- V only), and the complete set of pairwise interactions between the lagged dependent variable and the continuous variables included in the previous control set; (3) previous control set plus school fixed effects. Specification (3) in Panels VI and VII are estimated using a linear probability model. Column (4) reports separate propensity score matching estimates for school breakfast and school lunch using the variables from model (2) in the propensity score model (estimated via probit). Standard errors from 100 bootstrap repetitions. N = 13,534. See text for more details.

Table 2. Results: Children by Risk Type Entering Kindergarten

	Normal Weight Range			Overweight or Obese Entering Kindergarten		
	OLS/Probit (1)	**School Fixed Effects (2)**	**Propensity Score Matching (3)**	**OLS/Probit (1)**	**School Fixed Effects (2)**	**Propensity Score Matching (3)**
I. BMI: Growth Rates						
School	0.013*	0.014*	0.017*	0.006	0.001	0.012‡
Breakfast	(0.003)	(0.004)	(0.005)	(0.006)	(0.007)	(0.007)
School	0.000	-0.004	0.001	0.000	0.000	-0.002
Lunch	(0.003)	(0.004)	(0.003)	(0.005)	(0.008)	(0.006)
II. Percentile BMI: Changes						
School	1.608†	2.096*	3.211*	-0.147	-0.482	0.227
Breakfast	(0.716)	(0.761)	(0.987)	(0.559)	(0.708)	(0.655)
School	-0.303	-0.800	0.042	-0.397	-0.589	-0.534
Lunch	(0.571)	(0.719)	(0.594)	(0.485)	(0.750)	(0.555)
III. Probability of Being Overweight						
School	0.124*	0.033*	0.032†	-0.046	-0.016	0.016
Breakfast	(0.042)	(0.012)	(0.015)	(0.065)	(0.024)	(0.021)
School	-0.011	-0.010	0.000	-0.016	-0.004	-0.012
Lunch	(0.035)	(0.012)	(0.010)	(0.057)	(0.025)	(0.018)
IV. Probability of Being Obese						
School	0.155†	0.022*	0.021†	0.032	0.011	0.101*
Breakfast	(0.061)	(0.007)	(0.009)	(0.058)	(0.025)	(0.026)
School	0.008	-0.004	0.001	0.027	0.003	-0.019
Lunch	(0.053)	(0.006)	(0.005)	(0.050)	(0.027)	(0.022)

NOTES: ‡ p<0.10, † p<0.05, * p<0.01. Standard errors in parentheses. N = 10,039 (Normal) and 3,495 (Overweight or Obese). Specification (1) is identical to Specification (1) in Table 1; Specifications (2) and (3) are analagous to Specifications (3) and (4) in Table 1. Specification (2) in Panels III and IV is estimated using a linear probability model; in addition, these models exclude lagged values of the dependent variable in Model A since there is no variation by construction. See Table 1 for additional details.

Table 3. Selection into School Nutrition Programs

	Full Sample			Risk Type					
				Normal Weight Entering Kindergarten			Overweight or Obese Entering Kindergarten		
	OLS (1)	School Fixed Effects (2)	Propensity Score Matching (3)	OLS (1)	School Fixed Effects (2)	Propensity Score Matching (3)	OLS (1)	School Fixed Effects (2)	Propensity Score Matching (3)
I. Weight (lbs.)									
School	0.038	0.053	0.371	0.069	0.065	-0.101	-0.089	0.098	1.034‡
Breakfast	(0.154)	(0.175)	(0.313)	(0.091)	(0.104)	(0.171)	(0.328)	(0.411)	(0.620)
School	0.134	0.147	0.003	0.056	0.014	0.108	0.242	-0.081	-0.298
Lunch	(0.125)	(0.170)	(0.210)	(0.073)	(0.098)	(0.137)	(0.284)	(0.437)	(0.526)
N		13534			10039			3495	
II. Weight (lbs.): Change in Levels									
School	0.067	0.084	0.402	0.098	0.096	-0.055	-0.074	0.103	1.166‡
Breakfast	(0.154)	(0.175)	(0.274)	(0.091)	(0.104)	(0.177)	(0.328)	(0.412)	(0.651)
School	0.137	0.151	0.011	0.058	0.022	0.110	0.196	-0.097	-0.339
Lunch	(0.125)	(0.171)	(0.180)	(0.073)	(0.099)	(0.105)	(0.284)	(0.437)	(0.486)
N		13534			10039			3495	
III. Weight (lbs.): Logs									
School	0.001	0.001	0.007	0.002	0.002	-0.002	-0.002	0.000	0.016
Breakfast	(0.003)	(0.003)	(0.006)	(0.002)	(0.002)	(0.004)	(0.005)	(0.007)	(0.012)
School	0.003	0.003	0.001	0.001	0.000	0.003	0.004	0.000	-0.004
Lunch	(0.002)	(0.003)	(0.004)	(0.002)	(0.002)	(0.003)	(0.005)	(0.007)	(0.008)
N		13534			10039			3495	
IV. Weight (lbs.): Growth Rates									
School	0.011*	0.012*	0.021*	0.013*	0.014*	0.014	0.004	0.007	0.030‡
Breakfast	(0.004)	(0.004)	(0.009)	(0.004)	(0.004)	(0.009)	(0.007)	(0.008)	(0.016)
School	0.002	0.003	0.003	0.001	0.002	0.003	0.003	-0.001	-0.006
Lunch	(0.003)	(0.004)	(0.005)	(0.003)	(0.004)	(0.006)	(0.006)	(0.009)	(0.011)
N		13534			10039			3495	

NOTES: ‡ p<0.10, † p<0.05, * p<0.01. Standard errors in parentheses. Specification (1) is identical to Specification (1) in Table 1, except all terms involving child's birthweight are omitted in Panels II and IV; Specifications (2) and (3) are similarly analagous to Specifications (3) and (4) in Table 1. In addition, all regressions include controls for child's height in fall kindergarten (plus higher order and interaction terms). See Table 1 and text for details.

Table 4. Sensitivity Analysis: Bivariate Probit Results with Different Assumptions Concerning Correlation Among the Disturbances

	Correlation of the Disturbances											
	Specification (1)						Specification (2)					
	$\rho = 0$	$\rho = 0.1$	$\rho = 0.2$	$\rho = 0.3$	$\rho = 0.4$	$\rho = 0.5$	$\rho = 0$	$\rho = 0.1$	$\rho = 0.2$	$\rho = 0.3$	$\rho = 0.4$	$\rho = 0.5$
	A. Probability of Being Overweight											
School	0.050	-0.117*	-0.284*	-0.449*	-0.614*	-0.778*	0.070†	-0.097*	-0.264*	-0.431*	-0.598*	-0.766*
Breakfast	(0.032)	(0.031)	(0.031)	(0.031)	(0.030)	(0.029)	(0.036)	(0.035)	(0.035)	(0.034)	(0.034)	(0.033)
School	-0.004	0.023	0.052†	0.082*	0.113*	0.145*	-0.013	0.015	0.044	0.074†	0.106*	0.139*
Lunch	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)	(0.030)	(0.030)	(0.029)	(0.029)	(0.029)	(0.029)
	B. Probability of Being Obese											
School	0.055	-0.112*	-0.278*	-0.444*	-0.608*	-0.771*	0.064	-0.103†	-0.270*	-0.436*	-0.603*	-0.770*
Breakfast	(0.035)	(0.035)	(0.035)	(0.034)	(0.033)	(0.032)	(0.041)	(0.041)	(0.040)	(0.040)	(0.039)	(0.038)
School	0.015	0.044	0.075†	0.108*	0.144*	0.182*	0.032	0.061‡	0.092*	0.125*	0.160*	0.199*
Lunch	(0.030)	(0.030)	(0.030)	(0.030)	(0.029)	(0.029)	(0.035)	(0.035)	(0.035)	(0.034)	(0.034)	(0.033)

NOTES: ‡ $p<0.10$, † $p<0.05$, * $p<0.01$. Standard errors in parentheses. Specifications (1) and (2) refer to control sets used in Table 1. See Table 1 and text for details.

Table 5. Sensitivity Analysis: Amount of Selection on Unobservables Relative to Selection on Observables Required to Attribute the Entire SBP Effect to Selection Bias

	Specification (1)			**Specification (2)**		
	Cov(ε,ν)÷ Var(ν)	**τ_1**	**Implied Ratio**	**Cov(ε,ν)÷ Var(ν)**	**τ_1**	**Implied Ratio**
BMI: Levels	14.625	0.290	0.020	0.453	0.209	0.460
		(0.092)			(0.056)	
BMI: Logs	0.654	0.014	0.022	0.024	0.010	0.405
		(0.005)			(0.003)	
BMI: Growth Rates	0.490	0.010	0.021	0.175	0.010	0.057
		(0.003)			(0.003)	
Percentile BMI: Levels	77.583	2.114	0.027	4.465	1.478	0.331
		(0.714)			(0.510)	
Percentile BMI: Changes	57.727	1.009	0.017	7.718	1.475	0.191
		(0.548)			(0.510)	
Probability of Being Overweight	3.313	0.019	0.006	0.327	0.019	0.058
		(0.011)			(0.009)	
Probability of Being Obese	3.450	0.015	0.004	0.456	0.012	0.027
		(0.009)			(0.007)	

NOTES: Standard errors in parentheses. Specifications (1) and (2) refer to control sets used in Table 1, plus NSLP participation. Cov(ε,ν)/Var(ν) refers to the asymptotic bias of the unconstrained estimate under the assumption of equal (normalized) selection on observables and unobservables. τ_1 refers to the unconstrained estimate of the effect of SBP participation. The implied ratio is the latter divided by the former. See Table 1 and text for details.