Childhood Overweight and School Outcomes

Minh Wendt[a] and Jean Kinsey[b]

[a]Economic Research Service, USDA
[b]Applied Economics, University of Minnesota

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Abstract

This paper investigates the association between weight and elementary school students' academic achievement, as measured by standardized Item Respond Theory scale scores in reading and math. Data for this study come from the 1998 cohort of the Early Childhood Longitudinal Study, Kindergarten-Fifth Grade (ECLS-K), which contains a large national sample of children between the ages of 5 and 12. Estimates of the association between weight and achievement were obtained by utilizing two regression model specifications, a mixed-effects linear model and a student-specific fixed-effects model. A comprehensive set of explanatory variables such as a household's motivation in helping the student learn (e.g. parents' expectations for their child's schooling and levels of parental involvement with school activities), teacher qualification, and school characteristics are controlled for. The results show that malnourished children, both underweight and overweight, especially obese, achieve lower scores on standardized tests, particularly for mathematics, when compared to normal weight children. The outcomes are more pronounced for female students compared to male students. These results emphasize the need to reduce childhood malnutrition, especially childhood obesity.

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Background

Early childhood nutrition is one of the most important factors contributing to subsequent academic achievement. Poor nutrition during the brain's most formative years has been shown to score lower on tests of vocabulary, reading, math, and general knowledge (Brown and Pollitt 1996). Childhood malnutrition, or as some researchers refer to it as "misnourishment", can be observed in two forms: underweight and overweight. Although a surge in the prevalence of childhood obesity over the last several decades has drawn most of the concerns, there still exists a problem of underweight in children, particularly for minority groups in the U.S. (CDC 2006).

Overweight rates in U.S. children and adolescents 6–11 years of age have more than tripled in the last 3 decades, from 4.2% in the 1970s to 18.8% in 2003–04 (CDC 2006). This phenomenon disproportionally affects minority groups. In the 2001–2004 period, 15.6% of white girls, 24.8% of African American girls, and 16.6% of Mexican girls were overweight. Moreover, the extent to which children's body mass index (BMI)[1] exceeds the overweight threshold is also increasing at a faster rate during the same time period (Jolliffe 2004).

On the other hand, although the overall prevalence of underweight in children from birth to age 5 has been decreasing, from 6.7% in 1993 to 5.9% in 1998, and down to 4.5% in 2007, the prevalence is still high among African American (5.9%) and Asian/Pacific Islander (6.1%) in 2007 (Polhamus et al. 2009).

A growing body of evidence suggests that childhood overweight is detrimental to not only children's physical health but also significantly influence their psychological and cognitive

[1] BMI is defined as the weight (in kilograms) divided by height (in meters) squared. Equivalently, the weight (in pounds) divided by height (in inches) squared and multiplied by 703

functioning in the long run (Falkner et al. 2001, Crosnoe and Muller 2004, Datar et al. 2004, Datar and Sturm 2006, Averett and Stifel 2006).

While the correlation between childhood overweight and physical health problems is well known, the link between childhood overweight and academic achievement is less obvious due to the complexity of the connection. Direct effects of malnutrition on cognitive functioning might be due to lacking certain types of crucial macronutrient such as protein (Hoorweg and Stanfield 1976, Grantham-McGregor et al. 1999a) or vitamins and mineral such as iron (Halterman et al. 2001; Lozoff et al. 2000, Nead et al. 2004) and iodine (Grantham-McGregor et al. 1999b). Indirect effects of malnutrition on cognitive functioning include poor health, certain types of illness (e.g. diabetes, sleep apnea, breathing problems), psychological problems (e.g. self-esteem, isolation, and depression) (Tauman and Gozal 2006), and social skills (interpersonal skills, self-control, external behaviors (Datar and Sturm 2004; Gable et al. 2009).

In this paper, we examine the hypothesis that both childhood underweight and overweight (and obese)[2] has a negative impact on academic outcomes in elementary school children. This hypothesis has considerable policy interest because of its disheartening consequences. In the short run, this negative association might affect students' school attainment. In the long run, a rising prevalence of childhood overweight implies a significant increase in adult obesity. Consequently, the problems faced by obese adults are intensified if childhood obesity lowers

[2] We follow the CDC's categorizing guidelines for children age 2-19. Specifically, student's BMI scores are first converted to percentiles. If their scores are less than or equal to the 5th percentile, they are classified into the underweight category. Equivalently, students whose scores are between the 5th and 85th percentiles are considered to have normal weight; between the 85th and 95th percentiles are considered overweight; and greater than the 95th percentile is considered obese.

educational achievement, given the protective effects of education on health (Grossman 2006).

The entailed costs are not limited to health care but also economic costs of lower quality of life (private) and lower productivity (public) in the long run. Wang and Dietz (2002) estimated that the direct cost of childhood obesity in the U.S. is around US$127 million in the late 1990s, which amounts to 1.7% of annual total US hospital costs.

Household and Educational Production and Childhood Overweight

The literature on the direct link between children's BMI and cognitive growth is sparse. Theoretically, this topic is at the crux of two related but different strands of literature. The early childhood development branch of literature seeks to understand the role of parents and home environment in producing children's cognitive skills. The educational production branch examines the effects of teacher and school resources on student's academic outcomes. Furthermore, empirically data are often limited to one domain, either parents and home characteristics only or school environment only.

The existing empirical evidence linking childhood obesity and academic performance is weak, particularly after household economic status is controlled for. Several cross-sectional studies find a positive correlation between childhood obesity and grade retention (Tershakovec et al. 1994), and the likelihood of children being placed in special education or remedial class (Falkner et al. 2001). Another cross-sectional study by Li et al. (2008) finds that the association between BMI and academic performance is not significant after adjusting for family characteristics, but measures of cognitive functioning remain significantly and negatively associated with BMI scores among children.

Other longitudinal studies (Datar et al. 2004; Datar and Sturm 2006; Averett and Stifel 2007) with nationally representative samples of U.S. children between the ages of five and eight by find that overweight children have significantly lower mathematics and reading scores compared to normal weight children in kindergarten; this relationship persists through the end of first grade. The effect is greater for girls than boys. A shortfall of these studies is that they do not control for teacher and/or school inputs, which have been shown in the literature to be important factors of student academic achievement (Darling-Hammond 2000, Rivkin et al. 2001, Krueger 2003).

This paper builds on previous studies and extends on current knowledge by combining the two strands of literature. Using an exceptionally rich dataset, Early Childhood Longitudinal Study – Kindergarten cohort (ECLS-K), we estimate the effect of student, household, and school inputs on student academic achievement. Due to the hierarchical structure of the dataset (students nested within schools), a mixed-effects linear model is used. In addition, to control for possible endogeneity problems[3], we also utilize a student-specific fixed-effects model. To the best of our knowledge, currently there exists no method to compare between these two models[4]. Our sample include a cohort of students entering kindergarten year 1998-1999 at the average age of 5-6 and proceed through 5th grade at age 10-12.

The Model

Household production and demand functions (Becker 1965) have been widely used in economics to study determinants of children's health and/or academic achievement in the

[3] There are two common endogeneity issues: simultaneity and reverse causality. Simultaneity refers to unobserved characteristics that simultaneously determine certain explanatory variables and the outcome. Reverse causality refers to the direction of causality which may go both ways regardless of unobservables. See Greene (2003) or Wooldridge (2002) for more detailed discussion on the endogeneity issue.

[4] This is not to be confused with a traditional random-effects models (not multilevels), for which there is a Hausman test to compare between random- and fixed-effects models.

U.S. (Senauer and Gracia 1991, Variyam et al. 1999, Averett and Stifel 2007). In this framework, households combine time, human capital, and purchased goods to produce goods such as cognitive skills of a child, so as to maximize a joint utility function. The market goods purchased by households (food, schooling expenses) derive their values by supplying characteristics (nutrients, knowledge) necessary for the production the good (cognitive skills). Subject to the household income, time, and technology constraints, household utility maximization generates demand functions for the inputs and characteristics, which contain only exogenous variables (Rosensweig and Schultz 1983, Senauer and Garcia 1991). In this framework, a cognitive skill production function for the ith child represented by test scores (TS_i) can be specified as

(1) $TS_i = f(C_i, H_i, I_i)$

where C_i is a vector of characteristics of the child such as the child's weight status, age, and gender, H_i is a vector of household characteristics such as family structures, parents' education and income, and I_i is an input vector to cognitive skills such as time spent in learning activities. However, this framework is restrictive in the sense that it views the household as the main input in producing the cognitive skill output of a child. Therefore, we further utilize the education production framework that is widely used in estimating the effectiveness of school resources on students' learning (Hanushek 1986).

The education production function is based on an analogy between the knowledge acquisition process of a human being and the production process of a firm. The goal is to understand the technology and efficiency of school inputs in producing students' cognitive achievement outputs. Although there are still debates on the effectiveness of certain components in the educational technology, the consensus is that both teacher characteristics

and qualifications and school resources are important input factors. In this framework, the output (test scores) can be specified as a function of several inputs

(2) $TS_i = g(C_i, I_i, T_i, S_i)$

where TS_i, C_i, and I_i are defined as above, T_i is the ith child's teacher characteristics, and S_i is school resources.

Combining all available elements that theoretically contribute to the achievement of the ith student, equations (1) and (2) may be expressed together as

(3) $TS_i = g(C_i, I_i, H_i, T_i, S_i)$

Data

The data used in this study comes from the U.S. Department of Education's Early Childhood Longitudinal Study, Kindergarten class of 1998–99 (ECLS-K). This dataset provides information required to understand children's health, early learning, development, and educational experiences. Data is collected about the child, the child's parents/guardians, teachers, and schools through direct child assessment and also through home and school interviews. The survey uses a multi-stage probability sampling design to ensure a nationally representative sample of children attending kindergarten in 1998-99, with an oversampling of Asian Pacific Islanders (APIs).

In the fall of 1998, approximately 24 kindergarteners were selected within each of the sampled schools. In total, 1,280 schools were sampled from the original frame, and 133 additional schools were selected in the subsequent freshened frame.[5] Of these, 953 were public schools and 460 were private schools.

[5] The sample was freshened in first grade (1999-2000 school year) to include students who were not sampled during kindergarten (1998-1999 school year). Such students include immigrants to the United States who arrived after fall 1998, students living abroad during the 1998-99 school year, students who were in first grade in 1998-99 and repeated it in 1999-2000, and students who did not attend kindergarten.

In the course of six school years, the number of children who participated in all four rounds of data collection is 10,590 students. This represents 46% of children sampled in the base year. Sample attrition was due mainly to children changing schools and to families moving outside of the PSUs or to areas where they could not be located. Approximately 50% of movers were followed by ECLS. For more details on sample attritions (including non-response and change in eligibility status over time) see Tourangeau et al. (2006).

In this paper, we consider 4 rounds of data: round 1 corresponds to kindergarteners (which is a merge of 2 waves of data, one in the fall 1998 and one in the spring 1999), round 2 for first graders, round 3 for third graders, and round 4 for fifth graders. Therefore, the average time between rounds 1 and 2 is one year and the gaps between subsequent rounds are two years.

Variables

Dependent variables

ECLS-K students were tested on reading and mathematics during each data collection round using a two-stage assessment for each subject[6]. In the first stage, students received a 15–20 item routing test. Results from these routing tests led to the selection and administration of one of the alternative second-stage tests, which had items of appropriate difficulty for the ability level indicated by the first-stage (i.e., routing) test.

Since students do not necessarily take the same tests, item response theory (IRT) scores were computed for all students. IRT scores are the closest measure of the number of items students would have answered correctly if they had attempted all of the 186 reading questions and 153 mathematics questions in both stages in all rounds. IRT scoring makes possible the

[6] The assessment instruments and scale scores are designed and implemented by a collaboration of the U.S. Department of Education, National Center for Education Statistics (NCES), and Westat (consulting company). See Pollack et al. (2005) for more details.

longitudinal measure of gain in achievement over time, even with different assessment tests at each point in time. The reliability of IRT scores is high: .93 for reading and .92 for mathematics (Tourangeau et al. 2006).

Standardized IRT scale scores for reading and mathematics are used to measure students' direct cognitive skills. These scores serve as an indicator of students' performance relative to their peers. They have a mean of 50 and standard deviation of 10. That is, a standardized score of 60 on a reading test represents a reading proficiency at one standard deviation higher than the mean for a student in a given grade level, relative to the student population of the same grade represented by the ECLS-K study sample.

Since the principle interest of this paper is the relationship between childhood overweight and educational achievement, summary statistics for these two variables is presented in table 1, which shows the distribution of reading and math test scores by weight category and grade level, including a separate category for missing BMI data.

Table 1. Distribution of Weight Categories and Mean Test Scores, by Grade

	Kindergarten		1st grade		3rd grade		5th grade	
Reading	Num obs	Mean	Num obs	Mean	Num obs	Mean	Num obs	Mean
Underweight	464	50.667	430	51.825	270	52.491	252	51.889
Normal weight	10734	50.666	10347	51.545	7978	52.144	5997	52.811
Overweight	2054	49.962	1936	50.544	2004	51.617	1773	51.788
Obese	1595	48.323	2317	50.515	2458	50.502	2015	50.656
Missing	70	36.511	1000	51.801	507	51.107	226	51.625
Math								
Underweight	472	49.679	436	50.528	270	51.712	253	51.739
Normal weight	11085	50.861	10513	51.434	8004	52.139	5998	52.867
Overweight	2144	50.269	1977	50.631	2014	51.533	1777	51.688
Obese	1679	48.571	2384	49.729	2470	50.225	2017	50.568
Missing	68	38.279	1038	51.461	504	51.398	223	52.906

We observe from table 1 that the mean scores for overweight (OW) and obese (OB) students are lower than that of underweight (UW) and normal weight (NW) students for

reading. However, math scores are generally higher for NW students compared to the other 3 weight categories.

Except for the kindergarten year, the mean scores for the missing BMI category are not significantly different[7] from that of the normal or overweight categories. Therefore, it should not cause major concern in terms of the biasness of missing data patterns.

Independent variables

The explanatory variables in our regression models are divided into four categories: characteristics of the child, parents and households' factors, teachers' inputs, and schools' resources. The explanatory variable of interest is a student's weight status. Raw scores of students' BMI collected by ECLS-K are converted to percentiles according to students' age and gender, and consequently to four weight categories: underweight, normal weight, overweight, and obese according to the CDC guidelines. Since both underweight and overweight (and obese) students are considered a form of malnourishment, they are hypothesized to have a negative impact on cognitive skills in elementary school students.

The set of student characteristics included in the regression models capture student ability and motivation in learning: frequencies of the student's reading time per week outside of school setting, whether the student has any learning problem, has repeated a class from kindergarten through 5th grade, number of hours the student watches TV per day, number of hours the student receives child care (i.e. non-parental care) per week, whether the student enters kindergarten early, on time, or late for age, average number of times the student

[7] The result is due to using pairwise t-tests between the normal or overweight and the missing BMI category

changes school per year since kindergarten. Demographics such as the student' race and gender, and grade level are also controlled for in this study.[8]

Besides the socioeconomic indicators such as parents' education and household income, we also exploit an array of variables available in ECLS-K to control for home environment. Variables such as the level of parental involvement in students' school activities,[9] whether parents expect their children to at least finish college, maternal depression scores, and whether parents often use physical methods to discipline the student capture parents' motivation in helping children learn. These are important factors that often omitted from previous empirical work, most likely due to data limitation. By explicitly controlling for these motivation and other household factors, we could reduce the confounding effect of omitted variable bias.

Other factors that contribute to the learning environment at home for the student include whether the household has a computer for student's use, the number of siblings the student has, whether the student lives with a single mother, a single father, or adopt/foster parents are compared with those who live with both biological parents, and whether the household experiences some type of food insecurity.

Teacher characteristics are used to capture the effectiveness of teacher inputs in the education production framework. Teacher experience is expressed in two terms, number of teaching years and its square, to allow for nonlinear relationship with student outcomes. Whether a teacher has a Masters or professional degree is another indicator of a teacher's

[8] In exploratory regression, we also control for students' age. However, due to high level of collinearity between grade level and students' age, and since grade level reflects a more accurate picture on test scores, we drop the age variable and only control for grade level in all of our regressions.

[9] Involvement in school was measured by the number of different activities that parents have participated in since the beginning of the school year such as a general school meeting, scheduled parent-teacher conferences, general school or class events, parent group meetings, or volunteering at child's school.

experience and knowledge. The motivation factor is assessed by whether the teacher enjoys teaching. The teacher's gender and race are also included.

In addition to the dummy variable that differentiates private from public schools, there are six other school characteristics in our empirical models. One of the most important factors that need to be controlled for is the school's "average" performance. This factor is captured by using the percentage of students testing at or above grade level on nationally standardized tests. This variable is important in hierarchical linear modeling since it represents the mean level of achievement of each school.

High turnover rates among teachers have been documented as a negative factor in students' academic achievement (Rivkin et al. 2005). A dichotomous variable is used to indicate this problem in a given school. An index of security problems (e.g., gangs, drugs, and violent crimes) is used to capture an aspect of a school's safety environment. School's size, the percentage of minority students in a school, region and locality of schools are also controlled for.

Estimates

Two main econometric specifications are used to test the hypothesis of the effect of children weight status on cognitive outcomes: mixed-effects linear model (ME) and a student-level fixed-effects (FE) model. Within each model, there is a set of three regressions, one for each gender and one for the full sample.

Mixed-effects linear model (ME)

The ME model accommodates the hierarchical structure of the dataset (several observations for each student and a cluster of students in a school) by adequately dealing with the correlation between observations within the same cluster level. Specifically, the ME

model addresses the nested structure of the data by including two random intercepts, one for schools and the other for students within a school (Rabe-Hesketh and Skrondal 2008). The fitted ME model correspond to equation (3) is as follows:

$$
(4)\quad
\begin{aligned}
&\mathrm{Y_{itk}} = \beta'\mathrm{C_{itk}} + \delta'\mathrm{P_{itk}} + \varphi'\mathrm{I_{itk}} + \eta'\mathrm{T_{itk}} + \gamma'\mathrm{S_{ik}} + \varsigma_{ik}^{(Student)} + \varsigma_{k}^{(School)} + \varepsilon_{itk} \\
&\varsigma_{ik}^{(Student)} \sim N(0, \psi_{Student}) \\
&\varsigma_{k}^{(School)} \sim N(0, \psi_{School}) \\
&\varepsilon_{itk} \sim N(0, \theta^2 I)
\end{aligned}
$$

where $\mathrm{Y_{itk}}$ is reading or math test scores for the ith student at t^{th} round in k^{th} school, $\mathrm{C_{itk}}$ is a vector of student demographics such as gender and race, $\mathrm{P_{itk}}$ is a vector of parents and household characteristics such as motivation to help a child learn, $\mathrm{I_{itk}}$ is a vector of other cognitive skills inputs such as frequencies of reading activities, $\mathrm{T_{itk}}$ is a set of teacher characteristics such as experience and qualification, and $\mathrm{S_{ik}}$ is a vector of school factors that contribute to a student's academic achievement such as teacher's turnover rates and school security problem. $\varsigma_{ik}^{(Student)}$ and $\varsigma_{k}^{(School)}$ are the intercepts that represent student- and school-level random effects, and ε_{itk} is the error term.

The random intercept $\varsigma_{ik}^{(Student)}$ captures any student-specific but unobserved characteristics of each student in k^{th} school. It is assumed to vary across students in the sample data with variance ψ_{Student}. That is, $\varsigma_{ik}^{(Student)} \mid \mathrm{X} \sim \mathrm{N}(0, \psi_{\mathrm{Student}})$. The random intercept $\varsigma_{k}^{(School)}$ captures any school-specific but unobserved characteristics of each school. $\varsigma_{k}^{(School)}$ is assumed to vary across schools in the sample data with variance ψ_{School}. That is, $\varsigma_{k}^{(School)} \mid \mathrm{X} \sim \mathrm{N}(0, \psi_{\mathrm{School}})$.

The intra-class correlation for the ith student between two time periods is

(5) $$\rho_{Student} = \frac{\psi_{Student} + \psi_{School}}{\psi_{Student} + \psi_{School} + \theta}$$

The intra-class correlation for the kth school is

(6) $$\rho_{School} = \frac{\psi_{School}}{\psi_{Student} + \psi_{School} + \theta}$$

where θ is the measurement error variance. The command "xtmixed" in Stata 10 was used to fit this model.

Student-level fixed-effects model (FE)

In order to control for a potential endogenous problem – a common issue in non-experimental data – we also employed a fixed-effects model. Since there exists no test for a direct comparison between our main mixed-effects model and this FE one, the main purpose of reporting this FE model is to illustrate that our key variables (student weight status) remain significant in explaining the variation in educational outcomes, after purging student-level unobserved effects. That is, the relationship between student weight status and school outcomes remains significant, regardless of estimating methods used.[10]

Empirical Results

Table 2 presents the descriptive statistics for the variables and regression results from the mixed-effects models for the full sample (both genders).[11] Although the results are generally similar between boys and girls at the elementary school level, there exist some differences that merit further discussion.

[10] As it is well known in the econometric literature, although a FE model relaxes the assumption of no correlation between individual-level effects and the set of explanatory variables (which is the source of possible endogeneity), it has two serious disadvantages. First, a FE approach does not produce any estimates for time-invariant variables such as student gender, race, and other factors such as whether a child enter kindergarten on time, later, or earlier for age. Second, FE approach is supposed to produce consistent and unbiased results at the price of efficiency. This is because it discards any information about differences between individuals in the data. Most importantly, the traditional FE approach can not accommodate hierarchical data.

[11] Results for separate regressions of each gender are available from the authors upon request

Table 2. Descriptive Statistics and Estimates of the Mixed-effects Models on Reading and Mathematics Scores

(1)	(2)	(3)	(4)	(5)
Variables description	Mean	Standard deviation	Reading estimate	Math estimate
Achievement				
Reading	52.199	9.209		
Mathematics	52.311	9.269		
Students' characteristics				
The student is underweight (=1; 0 otherwise)	0.027	0.161	-0.386	-0.758**
			(0.311)	(0.301)
Student is overweight (=1; 0 otherwise)	0.147	0.354	-0.250*	-0.322**
			(0.146)	(0.142)
The student is obese (=1; 0 otherwise)	0.149	0.356	-0.308*	-0.338**
			(0.167)	(0.166)
The student reads 3 or more times per week (=1; 0 otherwise)	0.741	0.438	1.863***	
			(0.113)	
Student has learning problems (=1; 0 otherwise)	0.246	0.431	-0.991***	-1.122***
			(0.118)	(0.114)
The student ever repeats a class from kindergarten through 6th grade	0.007	0.083	-5.930***	-5.779***
			(0.586)	(0.554)
Average number of hours the student watches TV per day (0-8)	1.892	1.122	-0.081*	-0.129***
			(0.048)	(0.047)
Average number of non-parental care hours per week (0-146)	5.416	9.406	-0.018***	-0.006
			(0.006)	(0.005)
The student's grade level (kindergarten - 6th grade)	2.234	1.928	5.884***	4.751***
			(0.273)	(0.266)
The student enters kindergarten late for age	0.076	0.266	0.585**	0.990***
			(0.260)	(0.272)
The student enters kindergarten early for age	0.014	0.118	-0.963*	-1.827***
			(0.553)	(0.575)
Change schools less than twice per year since kindergarten	0.065	0.247	-0.292	-0.210
			(0.212)	(0.207)
Change schools at least twice per year since kindergarten	0.009	0.093	0.444	0.507
			(0.521)	(0.503)
The student is Asian (=1; 0 otherwise)	0.046	0.211	0.891***	0.974***
			(0.341)	(0.355)
The student is African American/Black(=1; 0 otherwise)	0.096	0.295	-2.741***	-4.507***
			(0.283)	(0.293)
The student is Hispanic (=1; 0 otherwise)	0.133	0.339	-2.084***	-2.762***
			(0.241)	(0.249)
The student is from others ethnic groups (=1; 0 otherwise)	0.025	0.157	-1.436***	-1.783***
			(0.495)	(0.511)
The student is female (=1; 0 otherwise)	0.505	0.499	1.163***	-1.281***
			(0.137)	(0.142)
Parents' and households' characteristics				
An index of parents' involvement with the student's school activities (0-5)	3.525	1.213	0.168***	0.268***
			(0.048)	(0.046)
The student lives with a single mother (=1; 0 otherwise)	0.159	0.365	0.346*	0.397**
			(0.182)	(0.179)
The student lives with a single father (=1; 0 otherwise)	0.017	0.128	0.287	0.224
			(0.441)	(0.435)
The student lives with adopting or foster parent(s) (=1; 0 otherwise)	0.029	0.171	-1.016***	-1.608***
			(0.375)	(0.384)
Parents expect the student to at least finish college (=1; 0 otherwise)	0.774	0.418	1.830***	1.450***
			(0.132)	(0.128)
Maternal depression scores (0: none - 5: severe)	0.401	0.697	-0.161*	-0.053
			(0.087)	(0.086)
Parents use physical method to discipline the student (=1; 0 otherwise)	0.036	0.174	0.249	-0.134
			(0.287)	(0.275)
Number of sibblings the student has (0-14)	1.508	1.099	-0.602***	-0.268***
			(0.060)	(0.061)
Parents' highest level of education (0: HS or less - 1: BA/BS or higher)	0.407	0.491	1.464***	1.511***
			(0.090)	(0.091)

Annual household income less than $15,000 (=1; 0 otherwise)	0.084	0.278	-2.567***	-2.518***
			(0.279)	(0.273)
Annual household income $15,001-$30,000 (=1; 0 otherwise)	0.158	0.365	-1.763***	-1.638***
			(0.214)	(0.209)
Annual household income $30,001-$50,000 (=1; 0 otherwise)	0.249	0.432	-1.091***	-1.111***
			(0.170)	(0.167)
Annual household income, $50,001-$75,000 (=1; 0 otherwise)	0.217	0.413	-0.429***	-0.433***
			(0.152)	(0.147)
The household has food problem sometimes (=1; 0 otherwise)	0.078	0.268	0.045	0.089
			(0.216)	(0.210)
The household has a computer for student's use (=1; 0 otherwise)	0.774	0.418	0.810***	0.856***
			(0.135)	(0.129)
Teachers' characteristics				
Teacher enjoys teaching (=1; 0 otherwise)	0.928	0.258	0.020	0.148
			(0.180)	(0.172)
Teacher's years of teaching	14.586	9.958	0.058***	0.021
			(0.018)	(0.017)
Teacher's years of teaching - squared	311.89	342.71	-0.001**	-0.001
			(0.001)	(0.000)
Teacher has at least a Master or professional degree (=1; 0 otherwise)	0.381	0.486	-0.047	0.223**
			(0.108)	(0.102)
Teacher is White (=1; 0 otherwise)	0.909	0.286	0.250	0.245
			(0.191)	(0.182)
Schools' characteristics				
Private school (=1; 0 otherwise)	0.239	0.427	1.133***	0.078
			(0.267)	(0.269)
Percentage of student in school testing at or above grade level	67.749	21.406	0.011***	0.018***
			(0.003)	(0.003)
A school experiences high teacher turnover rates (=1; 0 otherwise)	0.141	0.348	-0.143	0.138
			(0.152)	(0.144)
School's size (0: up to 149 - 4: 750 or more)	3.225	1.084	-0.005	-0.007
			(0.081)	(0.078)
Percentage of minority students in a school (0: <= 10% - 4: > 75%)	2.391	1.436	-0.321***	-0.195***
			(0.072)	(0.070)
A school experiences security problems (gang, drug, violent crimes)	0.697	0.977	-0.096	0.051
			(0.063)	(0.061)
Northeast	0.167	0.373	-0.583*	-0.247
			(0.317)	(0.323)
Midwest	0.319	0.466	-0.040	0.414
			(0.287)	(0.291)
South	0.313	0.463	0.286	0.484*
			(0.275)	(0.278)
School is in an urban area	0.358	0.479	0.227	0.379*
			(0.220)	(0.224)
School is in a rural area	0.252	0.434	-1.060***	-1.076***
			(0.263)	(0.266)
Round 2	0.252	0.434	28.922***	24.026***
			(1.354)	(1.317)
Round 3	0.252	0.431	22.907***	18.768***
			(1.082)	(1.053)
Round 4	0.252	0.424	11.321***	9.155***
			(0.555)	(0.539)
Constant	n.a.	n.a.	17.996***	24.770***
			(1.505)	(1.463)
Random-effects parameters				
Standard deviation of school constant			2.012	1.966
Standard deviation of student constant			5.813	6.401
Standard deviation of residual			4.786	4.371
Intra-class correlation for students within a school			0.067	0.060
Intra-class correlation for the same student over time			0.623	0.701
Number of school clusters			1566	1560
Number of students per school cluster			11283	11259
Number of student observations			19575	19544
Log likelihoood			-65560	-65172
Wald Chi-square			4546	3785

Standard errors in parentheses:* p<0.10, ** p<0.05, *** p<0.01

Mixed-effects linear model (ME)

The dependent variables are standardized reading and math scores, each with a separate equation presented in columns (4) and (5). Independent variables include four main groups: (1) students' weight status[12] and other characteristics, (2) parents and households' characteristics, (3) teachers' factors, and (4) schools' inputs.

Student weight status and other characteristics

In the full sample (both genders), overweight (OW) and obese (OB) students have lower reading scores compared to normal weight (NW) students, each by .3 units of standardized score. In the math equation, all three weight categories: underweight (UW), OW, and OB students achieve lower scores compared to NW students. UW students achieve about .8 units lower, while OW and OB students have about .3 units lower in standardized scores.

When each gender of students is assessed separately, although all three weight categories, UW, OW, and OB, are negative compared to NW students, the results from the reading equation are statistically significant for OB male students and not for OB female students. That is, OB male students have .5 unit lower in standardized reading scores compared to NW male students while OB female students perform about the same with NW female students.

In contrast, the lower and significant results from all three weight categories compared to NW students seem to fall squarely on female students in terms of math scores. In other words, differences in weight status only affect female and not male students in their math test scores. Table 3 presents the results breakdown by gender.

[12] Normal weight status is omitted

Table 3. Mixed-effects Models, Weight Status and Test Scores, by Gender

Variables description	Reading			Mathematics		
	Male	Female	Both	Male	Female	Both
Students' characteristics						
The student is underweight (=1; 0 otherwise)	-0.273	-0.461	-0.386	-0.626	-0.785*	-0.758**
	(0.464)	(0.417)	(0.311)	(0.440)	(0.408)	(0.301)
Student is overweight (=1; 0 otherwise)	-0.271	-0.259	-0.250*	-0.267	-0.378*	-0.322**
	(0.216)	(0.198)	(0.146)	(0.206)	(0.194)	(0.142)
The student is obese (=1; 0 otherwise)	-0.475*	-0.256	-0.308*	-0.389	-0.390*	-0.338**
	(0.252)	(0.224)	(0.167)	(0.249)	(0.223)	(0.166)

These results reinforce and are somewhat stronger than previous studies on several aspects. First, all the results interpreted here are from full models that control for an extensive set of explanatory variables including child and household characteristics as well as teacher and school factors. Second, they show a consistent pattern through different weight status classifications[13]. To illustrate, we will compare the results here with three other studies that use longitudinal data and various econometric methods to study the link between childhood overweight and academic outcomes.

Datar and Sturm (2006) investigate the same issue as in this study, using the same dataset, ECLS-K. Their results show that becoming OW between kindergarten entry and the end of third grade is associated with reductions in test scores in girls but not in boys. However, Datar and Sturm (2006) study is different from this paper in three important ways. First, the dataset they used was available up to third grade only. Second, the authors employed school-level random effects (school cluster) modeling while a multilevel cluster structure, both at the school- and student-level, is used in this paper. Third, we control for a more extensive set of variables. Important factors such as parents' expectation for and involvement

[13] We also considered changes in student weight status over time. In this setting, students who have been normal weight are used as a base to compare with students who become normal weight, become overweight, or have been overweight between given two rounds of data. There are two reasons that we preferred the contemporaneous weight status method. First, the two results are very similar. Perhaps this is because 85% of students do not change their weight status between consecutive rounds of data. Second, the role of weight status might be oversimplified, since we have to fuse four weight categories into two (UW together with NW and OW together with OB) to avoid the complexity of having two many categories (16 total) and many of them with zeros.

in student's schooling, teacher's characteristics, and certain school characteristics are not controlled for in the Datar and Sturm paper. In other words, since these variables could potentially capture the motivation factor that is confounding both the explanatory and dependent variables, not controlling for them could lead to omitted variables bias (see Greene 2003, section 8.2 or Wooldridge 2002, section 4.1 for a thorough discussion).

Averett and Stifel (2007) report a significant correlation between standardized BMI scores and math scores. This relationship is positive for UW children and negative for OW children. In contrast, using the same dataset as in Averett and Stifel (2007), Kaestner and Grossman (2008) showed that the significant difference in math test scores of UW and OB students compared to NW students diminishes as maternal characteristics are added into the cross-sectional regression results. That is, the results show no consistent evidence that being either UW or OB is associated with lower test scores. However, neither Averett and Stifel (2007) nor Keaestner and Grossman (2008) controls for teacher or school inputs, which theoretically have a strong impact on student achievement (Darling-Hammond 2000, Rivkin et al. 2001, Krueger, 2003).

For the rest of the controlled variables, the signs of all coefficients are generally in agreement with previous studies. As expected, students in higher grades outscore those in lower grades, with an average of 6 units in reading and 5 units in math for each grade level. Even after controlling for this variable, the results show that there are other motivation and/or impediment factors that affect a student's learning. The frequencies of reading by students outside of school settings are correlated with 1.9 units higher in reading scores. In contrast, students who have some type of learning problems and who have ever repeated a class from

kindergarten through 5th grade achieve lower scores, by about 1 and 6 units, respectively, in both reading and math compared to other students.

The more time students spent watching TV, the lower their reading and math scores. This observation is in line with previous studies that used the displacement theory to explain this association (Hancox et al. 2005; Zimmerman and Christakis 2005). However, several studies that control for the content of TV programs show that there might be a positive correlation between children's educational TV viewing and subsequent academic achievement (Anderson et al. 2001; Wright et al. 2001). The content of TV programs is not controlled for in this research.

The number of hours that students spent in child care settings is negatively correlated with their reading scores but not with their math scores. However, note that the sources of (non-parental) child care are not controlled for, and there is no indication of the quality of child care programs. That is, we only observe the negative effect of long hours spent in child care on lower reading skills. Generally, the literature on the effects of child care quality is much larger and more conclusive than the literature concerned with child care quantity, but the effects tend to diminish after kindergarten age, and vary across different socioeconomic groups (Belsky et al. 2006; Downer and Pianta 2006; Magnuson et al. 2006).

Whether students enter kindergarten early or late for age shows an effect on their test scores. Students who enter early achieve 1 unit lower in reading and 1.8 units lower in math scores, while students who enter kindergarten later for age have .6 units higher in reading and 1 unit higher in math scores compared to others who enter at the right age. This result is in line with several previous studies, albeit the large body of literature on this issue is controversial (Sweeland and De Simone, 1987; Breznitz & Teltsch, 1989; West et al. 2000).

Girls score higher than boys in reading (by 1.2 units) but boys have higher math scores than girls (by 1.3 units). It should not be surprising that the literature on this topic is controversial. A meta-analysis of 100 studies published between 1963 and 1988 (Hyde et al. 1990) reveals that there is no gender difference in mathematics—particularly in problem solving—between boys and girls at the elementary school level. In fact, girls show a slight superiority in computation skill. However, differences favoring men and math scores emerge in high school and in college. This is in contrast with many other studies (Benbow and Stanley 1983; Leahey and Guo 2001). The literature on reading skills is less controversial: girls tend to have higher levels of reading motivation than boys (Wigfield and Guthrie 1997; Wigfield et al. 1997).

A recent paper by Gable et al. (2009) finds that overweight girls are more likely to be rated by teachers as having poorer interpersonal skills, less self-control, and more externalizing behaviors than normal weight female peers. These associations are less obvious in boys, except for externalizing behaviors. These findings imply that girls are more likely to suffer from the social stigma of being overweight compared to boys. Hence, the results hint at the idea that negative social effects might explain part of the gender differences in academic achievement between boys and girls.

Parent and household characteristics

Students whose parents have at least finished high school, have high expectation for their children's schooling (i.e., that their children at least finish college), and are more involved in their children's school activities outperform their peers. In contrast, maternal depression seems to be deleterious to students' test scores, particularly for female students. These variables represent not only the capabilities but also parents' effort level and stimulation in

helping children learn. By explicitly controlling for part of this "motivation", which is often hypothesized to be a confounding factor, we might be able to partially reduce a source of potential bias in our regression models.

Students who live with both biological parents perform better than those who live with adopting or foster parent(s). Perhaps this variable signifies an aspect of household stability and support. However, children living with single mothers do slightly better in both reading and math while those living with single fathers perform about the same with children living with both biological parents. This result reinforces previous findings on the linkage between family structures and student's achievement (Lee, 1993; Zill 1996; Carlson and Corcoran, 2001).

The higher the number of siblings a student has, the lower his or her reading and math scores. This result is in line with perhaps one of the most robust effects in human capital studies across academic disciplines over the last few decades (Powell and Steelman 1990; Conley and Glauber 2005). The two most accepted explanations for this phenomenon are the confluence model (Zajonc and Markus 1975) and the resource dilution hypothesis (Anastasi 1956; Blake 1981). See Powell and Steelman (1990) for detailed discussion on these two explanations.

Similar to previous literature, household income level shows a strong correlation with academic outcomes of students. Compared to households with annual income of at least $75,000, students in households in any other income groups score lower, with students at the lowest income level scoring the lowest on both math and reading tests.

Students in households that have a computer also score higher in both tests compared to those who do not have a computer at home. The pair-wise correlations between parental

education and these household characteristics range from .31 to .39, which do not seem to cause multi-collinearity problems in all regressions.

Teacher characteristics

Teacher experience, measured by a teacher's years of teaching, is positively correlated with students' reading, but not math, scores. However, this relationship is non-linear. The squared term of this variable shows that students' scores decline slightly as the number of teaching years increase. On the other hand, teachers with at least a masters or professional degree are associated with their students' higher math scores but not reading scores. Comprehensive literature reviews by Darling-Hammond (1999) and Whitebook (2003) confirm the general consensus of teacher quality on student's achievement.

School characteristics

Private school[14] students achieve higher reading scores than public school students, but there is no difference in math scores. These patterns are consistently observed from longitudinal descriptive statistics of this dataset which has the latest round for eighth graders (Walston et al. 2008). The variable that indicates the percentage of students in school testing at or above grade level in standardized tests is an important factor because it represents the school-specific performance level. In other words, the higher the scores across a school, the higher the scores for individual students. This variable captures the often unobserved characteristics of school resources.

The result showing schools with higher percentage of minority students having lower scores corresponds with the observation that minority students achieve lower scores on both reading and math compared to white students. Students from schools located in rural areas

[14] Due to small sample size, we do not consider subcategories (by religions) of private schools

have lower scores compared to those from large town. In addition, students from urban schools perform slightly better in math. Other school factors such as whether a school experience high teacher turnover rates, security problems, or school size do not affect student performance.

Random-effects parameters

In the reading equation (Table 2) the standard deviation is 2.01 at the school level and 5.81 at the student level. That is, on average, schools vary from the population mean with a standard deviation of 2.01 points and students within a school vary from the school mean with a standard deviation of 5.81 points on standardized reading tests.

The correlation in test scores among students within a school is 0.07 and within a student is 0.62 (See equation (5) and (6) above). That is, the variation of reading scores over four rounds of data is due mostly to student characteristics (62%); only 7% is due to school factors. The rest is due to error terms (unobserved).

In the math equation, the standard deviation is 1.97 at the school level and 6.40 at the student level. The correlation among students within a school is 0.06 and within a student is 0.70. The likelihood ratio tests that measure the goodness of fit are significant in all models. Separate likelihood ratio tests are used to test the (joint) significance of the weight status variables. The results show that these weight variables play a significant role in explaining the variations among student achievement test scores.

Student-level fixed-effects model (FE)

As stated above, since there is no method that allows direct comparison between the ME and FE models, the results of FE will be discussed briefly for supporting purposes. Recall that the FE regressions essentially purge all individual-specific time-invariant characteristics, thus

they might be able to eliminate potentially unobserved confounding factors, at the price of efficiency. Therefore, it is not surprising to observe that there are only a few significant variables in this model. Table 4 presents the FE results breakdown by gender.[15]

Table 4. Student Fixed-effects Models, Weight Status and Test Scores, by Gender

Variables description	Reading			Mathematics		
	Male	Female	Both	Male	Female	Both
Students' characteristics						
The student is underweight (=1; 0 otherwise)	0.469	0.208	0.297	-0.080	0.091	-0.093
	(0.560)	(0.507)	(0.375)	(0.498)	(0.474)	(0.343)
Student is overweight (=1; 0 otherwise)	-0.087	-0.419	-0.242	-0.138	-0.800***	-0.453***
	(0.284)	(0.257)	(0.190)	(0.252)	(0.236)	(0.172)
The student is obese (=1; 0 otherwise)	0.247	-0.573*	-0.205	0.127	-0.780**	-0.313
	(0.426)	(0.337)	(0.265)	(0.375)	(0.310)	(0.239)

Overweight female students achieve lower math scores while OB female students achieve lower scores in both reading and math compared to NW students. Similar to the results from the ME model, the pattern of the negative correlation between OW and OB status and test scores seem to affect female students more than to male students.

Similar to the ME model, several student characteristics are significantly correlated with students' test scores. Positive correlation in the reading equation is found for the frequencies of students reading by themselves outside of school settings and students' grade level. These patterns are not significant in math equation. Negative correlation for both reading and math is found for students who ever repeat a class from kindergarten through 5th grade.

Parents' high level of expectation for their children's schooling is positively correlated with students' higher test scores. Perhaps this result reflects some level of unobserved heterogeneity in parent's expectation and thus motivation in helping children to learn over time. That is, parents' expectation for children's schooling might change over time, in corresponding with students' achievement. In addition, female students who live with

[15] Full results for this FE models are available from the authors upon request

adopting or foster parents have lower reading scores compared to other female students who live with both biological parents.

Two other variables emerge to be positively and significantly correlated with students test scores: a dichotomous variable indicating that parents often use physical method to discipline a student and another variable indicating that a household has food problem sometimes. The literature on the particular topic of the effects of physical vs. non-physical discipline on students' test scores is thin, although there is a large body of studies on parenting styles and students' academic achievement (Kellam et al 1998; Snyder 2001; Vitaro et al. 2006).

Our result of the positive and significant relationship between male students test scores and food insecurity status seems to be counterintuitive since several previous research shows either a negative link between food insufficiency and student test scores (Alaimo et al. 2001) or no relationship (Stormer and Harrison 2003). There could be some unobserved linkages between household characteristics and food security that are not controlled for in this study.

After accounting for student-specific effects, teacher and school characteristics seem to have little effects on student test scores. Math scores of female students are positively correlated with teacher qualification (those who have at least a Masters or professional degree) and those in schools with higher percentage of students testing at or above grade level. Students from schools that experience some level of security seem to do better in math compared to other schools.

Despite some differences in terms of significant levels, the signs of all variables are generally consistent between the two models. Also, both models indicate that there is a high level of student-specific unobservable effects. The time effects in both ME and FE models show an increase in both test scores in subsequent rounds of data from kindergarten.

Conclusion

Effective policies and programs to alleviate childhood obesity require an understanding of underlying determinants as well as consequences. This study adds to the rapidly expanding literature that has greatly increased our knowledge on this topic over the last several years.

Using a combination of the traditional household production framework (Becker, 1965) and the educational production framework (Hanushek 1986), this study analyzes the impact of students' weight status on their reading and math test scores. On the one hand, a mixed-effects linear model is used to account for the nested structure (students nested within schools) of the data used in our analysis. On the other hand, to control for possible confounding unobserved characteristics at the student level, we also utilize a traditional fixed-effect analysis. Since there is no test that allows direct comparison between the two econometric model specifications, we present and interpret the main model – mixed-effects – and discuss briefly the fixed-effect model for supporting purposes. A comprehensive set of student, parents, household, teacher, and school characteristics are included in all of the regressions.

The results show that both underweight and overweight (including obese) students achieve lower scores on standardized tests compared to normal weight students, particularly for math test scores. The results are more pronounced for female students. The frequency of reading time outside of school settings is positively correlated with students' reading scores. In contrast, the longer TV or child care hours (i.e., non-parental care), the lower the scores. Students who enter kindergarten later for age achieve higher scores compared to those who those enter early or at the right age.

Besides a student's weight status and activities, a set of household characteristics emerges as important variables in explaining the student's academic achievement. Students whose parents have a higher level of education (at least finish high school) and income, a high

expectation for their child's schooling, and a high level of involvement in their child's school activities achieve higher test scores. Students who live with adopting and/or foster parents, and students living with more siblings achieve lower scores than those who live with both biological parents. Maternal depression has a negative effect on female students' reading scores.

Teacher characteristics do not show a strong correlation with students' achievement with the exception of teacher experience (measured by the number of years teaching) and qualification (Masters or professional degree or higher). Experienced teachers are correlated with students' higher reading scores and teachers with higher degrees are correlated with students' higher math scores.

Several school characteristics are significantly correlated with student achievement. Private school students achieve higher reading scores but not math scores compared to public school students. Schools with a higher percentage of students who tested at or above grade level in standardized tests are positively related to individual students' scores. A larger percentage of minority students in schools are negatively correlated with students' test scores. This pattern is in agreement with the observation that all minority groups, except Asian students, have lower scores in both reading and math compared to white students.

In short, these results imply that academic achievement (reading and math scores) are importantly linked to childhood malnutrition, particularly for obese children. If malnourished children perform poorly on cognitive tests, and if this trend persists into adulthood, it is likely that they will be less productive adults. Clearly, the economic consequences of these problems, malnourishment and low productivity, are incurred at both individual and societal levels. The results in this study emphasize the need for reducing childhood malnutrition,

particularly childhood obesity. This task cannot be accomplished without a collaboration of efforts dealing with government policies, parents' commitments, and schools' involvement in addressing the childhood obesity problem.

Study limitation and future research

So far, there are only a few studies on the particular link between childhood obesity and educational outcomes. More studies are needed given the importance of the issue and the inconsistency of empirical evidence. Also, several related issues should be investigated further such as the mechanism mediating the effect of being overweight on students' test scores. For example, a constructed latent variables method might help us better understand the mechanisms through which childhood obesity affects educational outcomes in children and adolescents.

While trying to advance the literature, we would like to acknowledge several limitations of our study. While the mixed-effects model used in this study is valuable in incorporating the nested effects of the hierarchical data, it does not address the problem of potential endogeneity. The fixed-effects model is used to control for simultaneity but not reversed causality – the two common problems of endogeneity. Previous studies had used instrumental variables methods with limited success, perhaps because it is especially difficult to select valid instruments.

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