

**The Effect of School on Overweight in Childhood:
Gains in Body Mass Index During the School Year and During Summer Vacation**

by

Paul T. von Hippel, Ph.D. (Ohio State University)¹

Brian Powell, Ph.D. (Indiana University)²

Douglas B. Downey, Ph.D. (Ohio State University)¹

Nicholas J. Rowland, M.A. (Indiana University)²

¹Department of Sociology, Ohio State University, 300 Bricker Hall, 190 N. Oval Mall, Columbus OH 43210. Email: von-hippel.1@osu.edu, downey.32@osu.edu. Phone: 614.688-3768 (von Hippel), 614.292.1352 (Downey),. Fax: 614.292.6687.

²Department of Sociology, Indiana University, Ballantine Hall, 1020 E. Kirkwood Ave., Bloomington IN 47405-7103 (powell@indiana.edu, nirowlan@indiana.edu).

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Corresponding author: Contact von Hippel at the address above. If von Hippel is unavailable, contact Downey.

Structured abstract (159 words)

Objectives: To find out whether school or non-school environments contribute more to childhood obesity, we compared gains in body mass index (BMI) when school is in session (during the kindergarten and first grade school years) to gains when school is out (during summer vacation).

Methods. Twice-yearly BMI measurements were taken on 5,380 children in 310 schools as part of the Early Childhood Longitudinal Study, Kindergarten cohort (ECLS-K). We used these measurements to estimate BMI gain rates during kindergarten, summer, and first grade.

Results: BMI gain was typically faster and more variable during summer vacation than during the kindergarten and first grade school years. The difference between school and summer gain rates was especially large for three at-risk subgroups: black children, Hispanic children, and children who were already overweight at the beginning of kindergarten.

Conclusions: Although schools' diet and exercise policies may be less than ideal, it appears that early school environments contribute less to obesity than do non-school environments.

Introduction

Over the past two decades, the prevalence of obesity¹ among young US schoolchildren has tripled, from five percent to fifteen percent of the 6-to-11-year-old population.²⁻⁴ Obesity is especially common among young black and Hispanic schoolchildren, about twenty percent of whom are now overweight.³

In seeking to explain childhood obesity, some observers have pointed to schools, which have been described as “obesity zones.”^{5,6} Schools have been faulted for serving fattening lunches,⁷ for scheduling inadequate time for exercise,⁸ and for allowing packaged-food and -beverage companies to install vending machines.^{6,9,10}

Other observers, however, have pointed to influences outside the school walls. These scholars have suggested that childhood obesity arises from fast-food restaurants and high-calorie convenience foods,^{11,12} from housing developments without sidewalks or recreational areas,¹³ from excessive television viewing,¹⁴ and from reductions in parental supervision as a result of mothers entering the work force.¹⁵

Although all of these specific factors may have some effect, it is unclear in general whether childhood obesity arises primarily from school or non-school influences. This question is fundamental because it can help to focus future efforts. For example, if the major sources of obesity lie inside school walls, then interventions should focus on improving the school environment. On the other hand, if the major sources of obesity lie outside of schools, then interventions that improve or compensate for the non-school environment may seem more promising.

The main objective of this study is to compare school and non-school influences on children's body mass index (BMI) by estimating children's rates of gain when they are in school—during the academic year—and when they are out of school, during summer vacation.

Methods

Disentangling the effects of school and non-school environments poses a methodological challenge, since it is difficult to measure accurately all of the school and non-school influences on BMI. If a clinical trial were possible, though, we could simply use a crossover design in which every child was exposed to a period of school “treatment” and a period of non-school treatment.

Seasonal comparisons provide a practical approximation to such a crossover trial. During the school year, children are exposed to a mix of school and non-school influences, while during summer vacation, they are exposed to non-school influences alone.^{16,17} If obesity arises primarily from school influences, we would expect accelerated BMI gains during the school year. On the other hand, if obesity arises primarily from non-school influences, we would expect accelerated BMI gains during summer vacation.

Although seasonal comparisons are analogous to a crossover trial, there are important differences. In a crossover trial, different groups would be rotated through the school treatment at different times; in U.S. schools, by contrast, nearly all children are exposed to the school treatment at about the same time, so that the school “treatment” is confounded with the season of the year. A secondary issue is that some children attend school for part of the summer, so that that it is difficult to observe these children in a pure non-school environment. We excluded these children from our primary analyses; later, we will discuss secondary analyses that contrasted them with children who were on vacation during summer.

A later section discusses threats to validity in more detail. On the whole, we argue that the threats to validity are relatively minor compared to the advantages of the seasonal approach.

Data

To estimate school-year and summer changes in BMI, we use the *Early Childhood Longitudinal Study, Kindergarten Cohort (ECLS-K)*, a national survey administered by the National Center for Education Statistics, U.S. Department of Education.¹⁸ In the ECLS-K, 17,212 children in 992 schools were followed from the beginning of kindergarten to the end of first grade. BMI was measured at the beginning and end of kindergarten and at the beginning and end of first grade. The beginning-of-first-grade measurements were restricted to a random subsample of 5,380 children in 310 schools. Our analysis focuses on these children, since the beginning-of-first-grade measurement is essential to estimating summer BMI gains. Note that this subsample of 5,380 children, though smaller than the full sample of 17,212, is just as much a random sample of the population. Note also that, although the ECLS-K continued to follow children until the fifth grade, later BMI measurements were taken at longer two-year intervals and do not permit separate estimates of summer and school-year BMI gains.

Model

We estimated BMI growth by fitting a *multilevel model for change*,^{19,20} which nests BMI measurements (level 1) within children, and nests children (level 2) within schools (level 3). The multilevel approach allows us to model mean rates of BMI gain, as well as variations in gain rates within and between schools.

If children were measured on the first and last day of each school year, then BMI growth could be estimated simply by subtracting successive BMI measurements and dividing by the time elapsed between them. In the ECLS-K, however, each school was visited at a different time, and

measurements were taken, on average, in mid-October—a month-and-a-half after the beginning of the school year—and in early May, a month before school let out. The observed BMI gain between the spring of kindergarten and the fall of first grade, then, is not a clean measure of summer BMI growth, since the period between the spring and fall measurements includes, on average, two-and-a-half months of school as well as two-and-a-half months of summer vacation.

To compensate for measurement timing, our model adjusts for the difference between each measurement date and the beginning and end of kindergarten, summer vacation, and first grade. In effect, this adjustment extrapolates beyond the October and May BMI measurements to the measurements that *would* have been obtained had each school been visited on the first and last day of its school year.

More explicitly, at level 1 we modeled each BMI measurement as a linear function of the months that child c in school s has been exposed to KINDERGARTEN, SUMMER, and FIRST GRADE at the time t of measurement m :

$$BMI_{mcs} = \alpha_{0cs} + \alpha_{1cs} \text{KINDERGARTEN}_{tcs} + \alpha_{2cs} \text{SUMMER}_{tcs} + \alpha_{3cs} \text{FIRST GRADE}_{tcs} + e_{mcs} \quad (1).$$

Here the intercept α_{0cs} is (an extrapolation to) the child's BMI on the first day of kindergarten. The slopes α_{1cs} , α_{2cs} , and α_{3cs} are monthly rates of BMI growth during kindergarten, summer, and first grade. The residual term e_{mcs} is measurement error, i.e., the difference between measured BMI and true BMI. This measurement error can be estimated because each child was measured twice on each occasion. The measurement error has a standard deviation of about 0.1 BMI units, which constitutes less than 0.5% of the total variance in BMI; in other words, BMI measurements are more than 99.5% reliable. Given the reliability of BMI measurements, we could probably have neglected measurement error; nevertheless, our model carefully separates measurement error from variation in true BMI and BMI growth.

In vector notation, level 1 of the model can be rewritten as

$$BMI_{mtcs} = \text{EXPOSURES}_{tcs} \boldsymbol{\alpha}_{cs} + e_{mtcs} \quad (2),$$

where $\text{EXPOSURES}_{tcs} = [1 \text{ KINDERGARTEN}_{tcs} \text{ SUMMER}_{tcs} \text{ FIRST GRADE}_{tcs}]$, and $\boldsymbol{\alpha}_{cs} = [\alpha_{0cs} \alpha_{1cs} \alpha_{2cs} \alpha_{3cs}]^T$ is a parameter vector representing initial BMI and subsequent BMI growth rates during kindergarten, summer, and first grade.

Now levels 2 and 3 of the model break the parameter vector $\boldsymbol{\alpha}_{cs}$ into components:

$$\boldsymbol{\alpha}_{cs} = \boldsymbol{\gamma}_0 + \boldsymbol{b}_s + \boldsymbol{a}_c \quad (3),$$

where the first component $\boldsymbol{\gamma}_0 = [\gamma_{00} \gamma_{10} \gamma_{20} \gamma_{30}]^T$ is a *fixed effect* representing the grand average for the parameters $\boldsymbol{\alpha}_{cs}$. The second component $\boldsymbol{b}_s = [b_{0s} b_{1s} b_{2s} b_{3s}]^T$ is a *random effect* at the school level (level 3), representing the departure of school s from the grand average. The third component $\boldsymbol{a}_c = [a_{0c} a_{1c} a_{2c} a_{3c}]^T$ is a *random effect* at the child level (level 2), representing the departure of child c from the average for school s .

Levels 2 and 3 of the model can be expanded to include a vector of covariates \boldsymbol{X}_{cs} such as ethnicity and household income:

$$\boldsymbol{\alpha}_{cs} = \boldsymbol{\gamma}_0 + \boldsymbol{\gamma}_1 \boldsymbol{X}_{cs} + \boldsymbol{b}_s + \boldsymbol{a}_c \quad (4).$$

Here $\boldsymbol{\gamma}_1$ is a matrix of fixed coefficients representing the effects of \boldsymbol{X}_{cs} .

Equations (2) and (4) can be combined to give a single mixed-model equation

$$BMI_{mtcs} = \text{EXPOSURES}_{tcs} (\boldsymbol{\gamma}_0 + \boldsymbol{\gamma}_1 \boldsymbol{X}_{cs} + \boldsymbol{b}_s + \boldsymbol{a}_c) + e_{mtcs} \quad (5),$$

which shows explicitly how children's growth patterns are modeled using interactions between children's characteristics \boldsymbol{X}_{cs} and their EXPOSURES_{tcs} to kindergarten, summer, and first grade.

Missing-Data Strategy

Like most surveys, the ECLS-K has a substantial number of missing values. One-third of the sampled children were missing one or more BMI measurements, and a few heights and weights had to be deleted because of obvious recording errors. Not quite half the sampled children were missing covariates, or missing information about the timing of the BMI measurement relative to the beginning and end of the school year.

We filled in missing values using a *multiple imputation* strategy.^{21,22} Using the MI procedure in SAS 9.1, we replaced each missing value with ten random imputations, using a multivariate normal model that involved all of the variables in equation (5). (The interactions in equation (5) were coded and imputed like any other variable.²²) To account for the correlation between BMI measurements of the same child, we formatted the data so that all of a child's BMI measurements appeared on a single line, along with the other variables.²² Although the dependent variable (BMI) was used in the imputation model, we did not use the imputed BMI values in our analysis.²³ Imputed BMIs were not needed for analysis, since multilevel growth models do not require that every child provide a measurement on every occasion.²⁴ For example, if a child's BMI was measured on three of the four measurement occasions, these three occasions were used in the analysis, but an imputed value for the fourth occasion was not needed.

In general, multiple imputation is more efficient than deletion of incomplete cases, and is often less susceptible to bias as well. Nevertheless, some readers may find it reassuring to know that estimates obtained by deleting incomplete cases were similar to the estimates obtained from multiple imputation.

Results

BMI is defined as weight in kilograms divided by the square of height in meters. For 5½-year-old children of average height (1.12 meters), then, a difference of one BMI unit is a little more than a kilogram ($1.12^2=1.25$ kilograms).

Childhood BMI typically follows a J-shaped trajectory, falling until age 5 or 6, then rising until age 18 (and beyond).^{25,26} At the beginning of kindergarten, then, children are near lifetime lows for BMI and are just starting to gain BMI at a slow though increasing rate. The period from kindergarten to first grade may therefore seem an inauspicious time to study childhood obesity; however, small differences at this age predict larger differences later on. Five- and six-year-old with above-average BMI and BMI gains are at increased risk for adult obesity.²⁷

Average and variance of BMI and BMI gains

As detailed in Table 1, *average BMI growth is slower during kindergarten and first grade than during summer vacation*. Children begin kindergarten with an average BMI of 16.205, then gain an average of .020 BMI units per month during kindergarten, .076 BMI units per month during summer vacation, and .033 BMI units per month during first grade. These average gain rates are plotted at the bottom of Figure 1. During the summer, average BMI gains are more than twice as fast as they are during either school year; the mean difference between summer and kindergarten is .056 BMI units per month, and the mean difference between summer and first grade is .043 BMI units per month (both $ps<.01$). These differences suggest that, for the “average child,” the school environment is less conducive to rapid BMI growth than is the non-school environment.

←Figure 1 near here→

Since the “average child” is not overweight, we may be less interested in the average growth rate than in variation around the average. As it happens, variation in BMI growth is also smaller

during the school year than during summer vacation—implying that *exceptionally high (or low) rates of BMI growth are less likely when school is in session*. As Table 1 shows (bottom row), the standard deviation of BMI gains is .448 BMI units per month during summer vacation, but only .176 and .162 BMI units per month during kindergarten and first grade, respectively. Disaggregating the total variance into school-level and child-level components, we find that, at both levels, the variance of summer gains significantly exceeds both the variance of kindergarten gains and the variance of first grade gains (all $p < .001$).

In addition, *the deceleration of BMI growth during the school year is more pronounced for overweight children than for children of normal weight*. As Table 1 shows, at both the school and the child level, there is a negative correlation between initial BMI and BMI gains during kindergarten ($p < .001$). This implies that initially overweight children gain BMI more slowly during kindergarten than do children of average BMI. In addition, summer gains are negatively correlated with kindergarten and first grade gains ($p < .001$), suggesting that the children who gain BMI faster than their peers during summer vacation tend to gain BMI more slowly than their peers when school is in session.

To illustrate these patterns, Figure 1 plots, on a typical school calendar, the expected change in BMI for children who are overweight on the first day of kindergarten. Average BMI gaps between overweight, average, and underweight children grow rapidly during summer vacation, but grow more slowly (or even shrink) during kindergarten and first grade.

The negative correlations in Table 1 have a complementary implication for *underweight* children. Initially *underweight* children tend to gain BMI more quickly than their peers during the school year, and more slowly during summer vacation.

In sum, the results suggest that overweight, average, and underweight children all tend to display healthier growth patterns during the school year than during summer vacation.

Sociodemographic differences

We next ask whether the variation in BMI and BMI gains is related to the sociodemographic characteristics that past research has associated with obesity.^{3,15,30} To address this question, Table 2 adds to the model variables representing race and ethnicity, maternal education, family structure, poverty, age, and gender. While most of these variables have little relationship to seasonal BMI growth, the racial and ethnic patterns are significant and striking.

As shown in Figure 2, *small racial/ethnic gaps are already present before school begins*. On the first day of kindergarten, black children are, on average, .320 BMI units heavier than white children who are comparable on other variables ($p < .01$); similarly, Hispanic children are, on average, .472 BMI units heavier than comparable white children ($p < .001$).

←Figure 2 near here→

In addition, *racial/ethnic gaps in BMI grow only during summer vacation*. During summer vacation, average monthly gains for black and Hispanic children are, respectively, .073 and .069 BMI units faster than those for white children who are comparable on other variables (both $ps < .01$). During kindergarten and first grade, by contrast, average gains for black, white and Hispanic children are approximately equal.

These racial/ethnic patterns suggest that schools are not primarily responsible for the excess of obesity among black and Hispanic children. Schools cannot be responsible for BMI gaps on the first day of kindergarten, nor can schools be responsible for growth in BMI gaps during summer vacation.

Limitations and competing explanations

Our analyses are confined to the first two years of school, and it is possible that data on older children would show different patterns. In addition, since the data do not come from a randomized

experiment, we must consider competing explanations for the observed effects. Specifically, since exposure to the school environment is not distributed randomly across the year, it is possible that some variable other than schooling is responsible for the observed deceleration of BMI gains during the school year..

The most obvious competing explanations, however, seem relatively implausible. One competing explanation is maturation. In the early years of school, most children are gaining BMI at a slow but increasing rate,²⁵ so it is not surprising that BMI gains are slower during kindergarten than they are during later periods. Maturation, however, cannot explain the seasonal pattern of results; if only maturation were at work, we would expect a smooth acceleration in BMI growth—slow growth in kindergarten, faster growth during summer vacation, and faster growth still during first grade. But the observed results depart from this pattern; instead of a smooth increase, we see an increase in BMI growth from kindergarten to summer, and then a decrease from summer to first grade. Maturation, then, cannot explain why average BMI growth is faster during summer vacation than during first grade. In addition, maturation cannot explain why the *variation* in growth rates is larger during the summer than during either school year.

Another competing explanation is seasonal confounding. As remarked earlier, the major weakness of aseasonal research design is that all children are out of school at more or less the same time—that is, the treatment (schooling) is confounded with season. If BMI growth varies across seasons for causes other than schooling, then those causes will be hard to disentangle from the effect of schooling, and the average effect of schooling may be under- or overestimated.

Seasonal confounding, however, also seems unlikely to explain our results. To explain the observed patterns, a seasonal confounder would not only have to increase *average* BMI growth during the summer; it would also have to increase *variability* in summer BMI growth. It is hard to imagine a confounder that would affect variability in this way. Schooling, however, can plausibly

explain changes in variability. During summer vacation, every student is in a different environment, and there is tremendous variation from one non-school environment to another; during the school year, however, all students are in relatively similar environments, and this similarity tends to dampen variability.³¹

If there is a plausible confounder, it might be seasonal variation in metabolism. There is some evidence that sleeping metabolic rates, at least among adults, decline a bit during the summer, perhaps because less metabolic energy is needed to maintain body temperature.³² Again, though, this decline in summer metabolism could only explain an increase in *average* BMI growth; it cannot explain the observed increase in the *variability* of BMI growth. In addition, a metabolic explanation fails to square with the weight-gain patterns of adults, who gain weight fastest not during summer, but during the winter holidays.³³ Although adults' metabolisms are relatively quick during the winter holidays, their diet and exercise patterns may be relatively unhealthy.

If we focus on environmental explanations, our findings for children are quite consistent with earlier findings for adults. Children gain BMI fastest during summer vacation, while adults gain weight fastest during the winter holidays. Putting these findings together suggests the plausible conclusion that, in general, *people are most likely to gain weight when they are in relatively unstructured environments—i.e., on vacation.*

Remaining questions

Like any research, this study raises questions that the data cannot fully answer. For example, *why* do children tend to gain BMI faster during summer vacation? Do children eat more in the summer? Do they exercise less? Unfortunately, the survey that we used (ECLS-K) contains little pertinent information on these questions. Measures of consumption and exercise were very crude, and were not measured in a consistent way across seasons. During the school year, for example, the

survey tells us which children ate school lunches and how many hours children spent in physical education class; during the summer, however, the survey tells us which children ate dinner with their families and which children participated in organized sports. Using this information, it is impossible to make informative comparisons between summer and school-year patterns of exercise and eating. (A different survey suggested that children consume about the same amount during the summer and the school year,³⁴ but that survey was based on self-report, which tends to underreport overeating.³⁵)

Another question is whether particular school policies are responsible for reducing BMI growth. This question lies beyond the scope of our study, which is designed to detect differences between school and non-school environments, rather than differences between one school's policies and another's. Past research, using a different design to study the same data, suggested that increasing physical education hours could reduce the BMI gains of overweight girls, but overweight boys and children of normal weight seemed unaffected.³⁶

A final question is whether summer BMI growth would be reduced if children spent the summer in a school environment. Here the survey provides some information, but not enough to answer the question with confidence. Children do not attend summer school at random, and relatively few spend much of the summer in school. Although eleven percent of the surveyed children attended summer school, only one percent were in summer school for more than half of the usual summer vacation. In addition, just three percent of the children attended year-round schools. In supplemental analyses (available from the authors), we compared year-round and summer-school children to children who spent the summer on vacation (controlling for the other variables in Table 2). The results were ambiguous. During summer, the estimated effect of attending year-round school was $-.201$ BMI units per month ($p < .01$, 95% CI: $-.348$ to $-.065$), while the estimated effect of attending summer school was just $-.005$ BMI units per month ($p = .9$, 95% CI: $-.102$ to $.092$). Both point estimates were negative, as expected, but only one was significantly different from zero, and

both confidence intervals were quite wide, indicating substantial uncertainty about the true effect of attending school during summer. Future research can reduce this uncertainty by collecting larger samples of children in summer school and year-round school.

Conclusion

Do schools contribute to childhood obesity? They may, to some degree, but it appears that other factors are more to blame. Our results show that most children—and especially children with a high risk of obesity—are more vulnerable to excessive BMI gain when they are out of school during summer vacation than when they are in school during fall, winter, and spring. Although schools may not provide ideal environments for healthy BMI growth, it appears that schools are better than many children’s non-school environments.

How do schools inhibit BMI growth? Although the data cannot answer this question directly (see above), we conjecture that the structured nature of the school day, with scheduled exercise periods and limited opportunities to eat, helps students to maintain a healthy BMI. By contrast, we speculate that many nonschool environments are relatively unstructured and unsupervised, allowing children to indulge in sedentary activities and excessive snacking. (A similar difference between structured and unstructured environments may explain why adults eat more on weekends than on weekdays,³⁴ and why adults gain weight faster during the winter holidays than at other times of year.³³)

These patterns have important implications for policy researchers interested in reducing childhood obesity. The first implication is that *policies which increase children’s exposure to school environments (e.g., after-school programs, extended school years, or year-round school) may have the potential to reduce childhood obesity*. A second implication is that *interventions that focus*

exclusively on improving unhealthy aspects of the school environment—for example, removing soft-drink vending machines—may be expected to have limited effects, since the major sources of obesity lie outside the school walls.

This does not mean that school-based interventions are doomed to failure. Rather, it suggests that policies which merely improve the school environment may be less effective than policies which improve or compensate for unhealthy non-school behaviors. Lessons on nutrition, for example, may improve children's out-of-school eating habits, particularly if parents are involved.³⁷ Likewise, physical education courses may be most beneficial for children whose out-of-school activities are sedentary. In short, perhaps the most productive interventions should target children's behavior not only during school hours, but also, and most importantly, after the bell rings.³⁸

About the authors: Paul von Hippel is Research Statistician in the Department of Sociology and Initiative for Population Research at Ohio State University. Brian Powell is Professor in the Department of Sociology at Indiana University. Douglas Downey is Associate Professor in the Department of Sociology at Ohio State University. Nicholas Rowland is a doctoral student in the Department of Sociology at Indiana University.

Contact information: Requests for reprints should be sent to Paul von Hippel (von-hippel.1@osu.edu, 614.688-3768, fax 614.292.6687) or Douglas Downey (downey.32@osu.edu, phone 614.292.1352, fax 614.292.6687).

Contributors: Von Hippel conducted the analyses and led the writing. Powell shared in the writing, framing, and interpretation. Downey conceived the study and shared in the writing, framing, and interpretation. Rowland led the literature review.

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Reference List

1. Terminology.
Notes: We use the terms “obese” and “overweight” interchangeably in this paper. Our definition of these terms is given in the caption to Figure 1. We recognize that there is disagreement over the definition of “obesity” for children and whether this term is appropriate for children (see M. Guillaume, *Am. J. Clin. Nutr.* **70**, 126S-130S (1999)).
2. Taubes G. Weight increases worldwide? *Science*. 1998b;280:1368.
3. Ogden CL, Flegal KM, Carroll MD, Johnson CL. Prevalence and trends in overweight among US children and adolescents, 1999-2000. *J. Am. Med. Assn.* 2002;288:1728-32.
4. Taubes G. As obesity rates rise, experts struggle to explain why. *Science*. 1998a;280:1367-1368.
5. Carter RC. The impact of public schools on childhood obesity. *J. Am. Med. Assn.* 2002;288:2180.
6. Levin A. Schools are obesity zones because of marketing pressures. *Med. News Today*. 2004.
7. Whitmore D. Do School Lunches Contribute to Childhood Obesity? Paper Presented to the American Economics Association: Philadelphia, PA.
8. Nader P. Frequency and intensity of activity of third-grade children in physical education. *Arch Pediatr Adolesc Med.* 2003;157(2):185–190.
9. American Academy of Pediatrics. Soft Drinks in Schools. *Pediatrics*. 2004;113:152-154.
10. James J, Thomas P, Cavan D, Kerr D. Preventing childhood obesity by reducing consumption of carbonated drinks: cluster randomised controlled trial. *Brit. Med. J.* 2004;328:1237.
11. Brownell KD. Fast Food and Obesity in Children [Commentary]. *Pediatrics*. 2004;113:132.
12. Cutler DM, Glaeser EL, Shapiro JM. Why have Americans become more obese? *Journal of Economic Perspectives*. 2003;17(3):93-118.
13. Frank L, Andresen M, Schmid T. Obesity relationships with community design, physical activity, and time spent in cars. *American Journal of Preventive Medicine*. 27(2):87-96.
14. Robinson TM. Television viewing and childhood obesity. *Pediatr Clin North Am.* 2001;48(4):1017-25.
15. Anderson PM, Butcher KF, Levine PB. Maternal employment and overweight children. *Journal of Health Economics*. 2003;22(3):477-504.

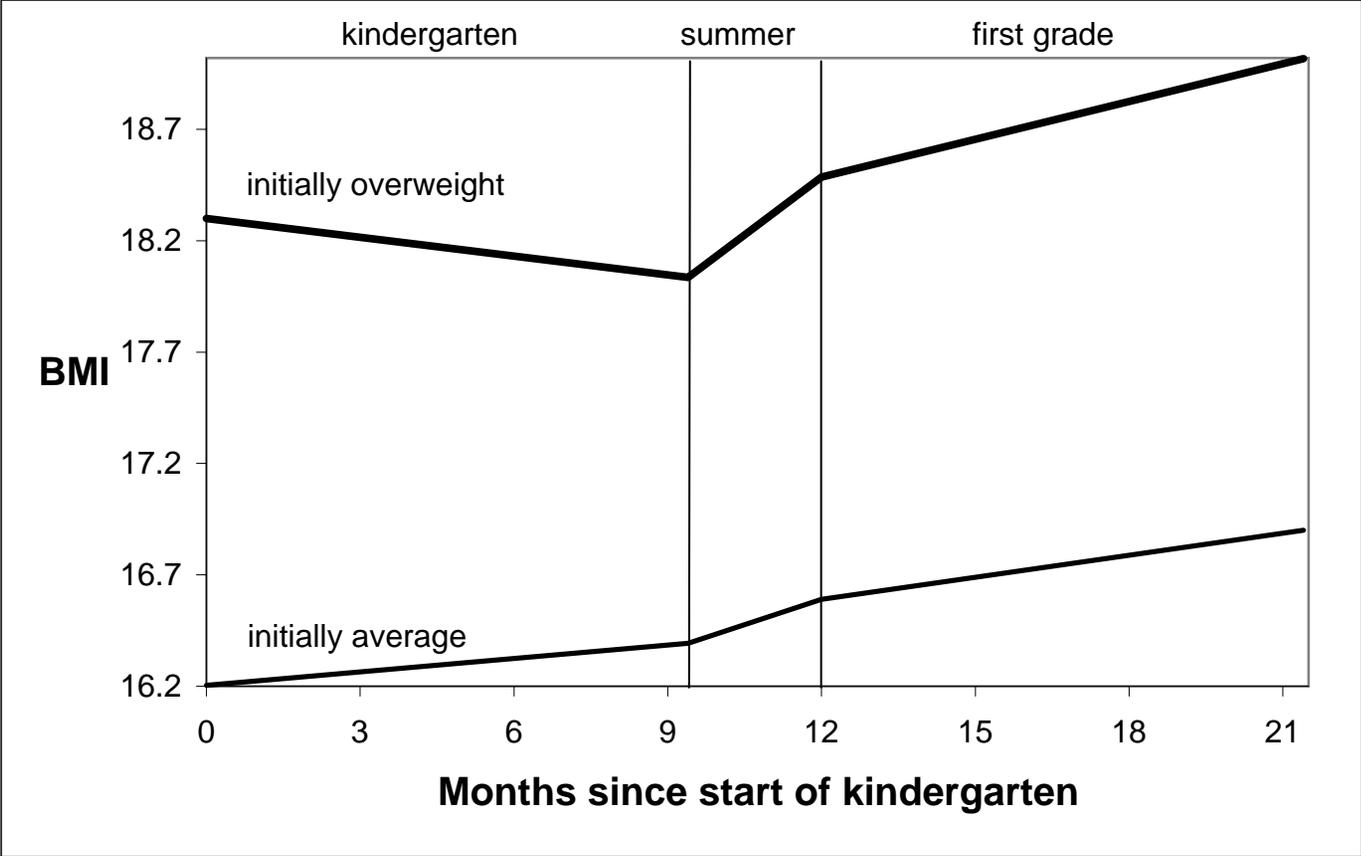
16. Entwisle DR, Alexander KL. Summer setback: Race, poverty, school composition, and mathematics achievement in the first two years of school. *Am. Soc. Rev.* 1992;**57**:72-84.
17. Heyns B; *Summer Learning and the Effects of Schooling*. San Diego: Academic Press; 1978.
18. National Center for Education Statistics. *Early childhood longitudinal survey, kindergarten cohort* . Washington, DC: 2003. See <http://nces.ed.gov/ecls/>.
19. Raudenbush SW, Bryk AS; *Hierarchical Linear Models: Applications and Data Analysis Methods*. 2nd ed. Thousand Oaks, CA: Sage; 2002.
20. Singer JD, Willett JB; *Applied longitudinal data analysis: Modeling change and event occurrence*. Oxford, UK: Oxford University Press; 2003.
21. Rubin DB; *Multiple Imputation for Survey Nonresponse*. New York: Wiley; 1987.
22. Allison PD; *Missing Data*. Thousand Oaks, CA: Sage; 2002.
23. von Hippel PT. Regression with Missing Ys: An Improved Strategy for Analyzing Multiply Imputed Data. Under review.
24. Raudenbush SW, Bryk AS; *Hierarchical Linear Models: Applications and Data Analysis Methods*. 2 ed. Thousand Oaks, CA: Sage; 2002.
25. Centers for Disease Control and Prevention. Body mass index-for-age percentiles: Girls, 2 to 20 years. 2000; accessed July 28, 2004. Web Page. Available at: www.cdc.gov/nchs/data/nhanes/growthcharts/set1/chart15.pdf.
26. Centers for Disease Control and Prevention. Body mass index-for-age percentiles: Boys, 2 to 20 years. 2000; accessed July 28, 2004. Web Page. Available at: www.cdc.gov/nchs/data/nhanes/growthcharts/set1/chart16.pdf.
27. Whitaker RC, Pepe MS, Wright JA, Seidel KD, Dietz WH. Early adiposity rebound and the risk of adult obesity . *Pediatrics*. 1998;101:e5.
28. Guillaume M. Defining obesity in childhood: current practice. *Am. J. Clin. Nutr.* 1999;70:126S-130S.
29. Kuczmarski RJ, Ogden C, Grummer-Strawn L, et al. CDC Growth Charts: United States. Advance Data Report No. 314. Vital and Health Statistics of the Centers for Disease Control and Prevention, National Center for Health Statistics. 2000.
30. Strauss RS, Knight J. Influence of the Home Environment on the Development of Obesity in Children. *Pediatrics*. 1999;103:e85.
31. Downey DB, von Hippel PT, Broh B. Are schools the great equalizer? School and non-school sources of inequality in cognitive skills. *Am. Soc. Rev.* 2004;69:613-635.
32. Plasqui G, Kester ADM, Westerterp KR. Seasonal variation in sleeping metabolic rate, thyroid

- activity, and leptin. *Am. J. Physiol Endocrinal Metab.* 2003;285:E338-E343.
33. Yanovski JA, Yanovski SZ, Sovik KN, Nguyen TT, O'Neil PM, Sebring NG. A prospective study of holiday weight gain. *N. Engl. J. Med.* 2000;342:861-867.
 34. Haines PS, Hama MY, Guilkey DK, B.M. Popkin. Weekend eating in the United States is linked with greater energy, fat, and alcohol intake. *Obesity Rsrch.* 2003;11:945-949. Notes: Haines et al. defined summer as the three months period from June 21 to September 21. Using the same data, we obtained similar results when we defined summer according to the school calendar.
 35. Schoeller DA. How accurate is self-reported dietary energy intake? *Nutr. Rev.* 1990;48:373-379.
 36. Datar A, Sturm R. Physical education in elementary school and body mass index: Evidence from the early childhood longitudinal study. *Am. J. Pub. Health.* 2004;94:1501-1506.
 37. Story M. School-based approaches for preventing and treating obesity. *International Journal of Obesity.* 1999;23:S45-S51.
 38. Conley D., K. Albright, eds.; *After the Bell: Family Background, Public Policy, and Educational Success.* Routledge; 2004.

Figure captions

Figure 1. Expected BMI changes for children of average BMI, and for children who are overweight at the beginning of kindergarten. The plot uses an average school calendar, with 9.4 months of kindergarten followed by 2.6 months of summer and 9.4 months of first grade. To draw the average trajectory, initial BMI was set to 16.2, which is the average from Table 1. To draw the trajectory for overweight children, initial BMI was set to 18.3; this value was determined using the US convention²⁸ that the threshold for overweight is the 95th percentile on the CDC's BMI-for-age charts. (The BMI-for-age charts describe the distribution of children's BMI before recent increases in obesity.²⁹) At 5½ years—the average age at the beginning of kindergarten—the 95th percentile for BMI is 18.1 for boys and 18.5 for girls; the overweight child in Figure 1 is midway between these values, with an initial BMI of 18.3. The trajectories shown here can be calculated using the estimates in Table 1; calculations are available from the authors.

Figure 2. Average BMI growth for black, white, and Hispanic children who are equal on other variables.



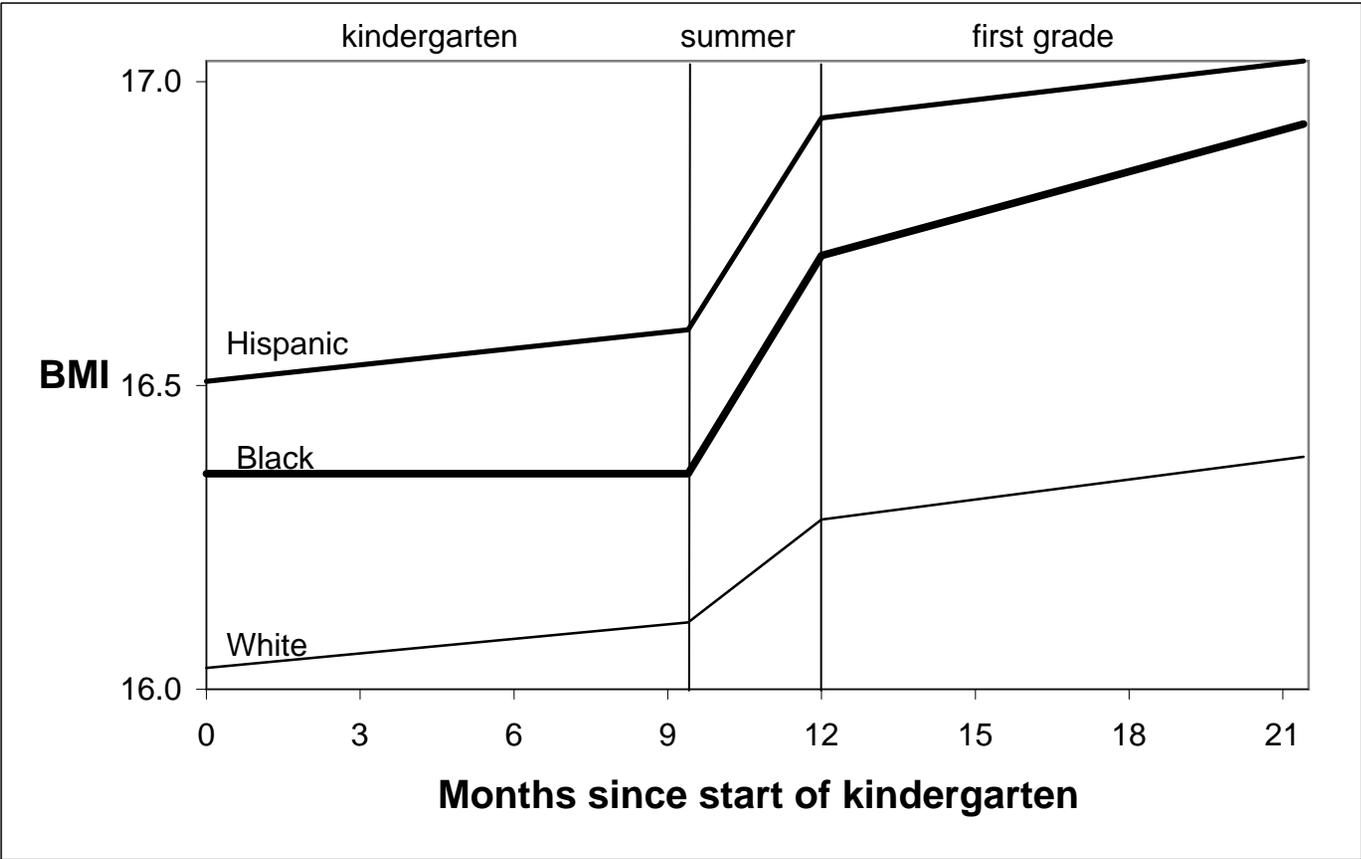


Table 1. Means and variance components for initial BMI and subsequent BMI gains.

		Monthly BMI gain				Contrasts	
		Initial BMI	Kindergarten	Summer	First grade	Summer minus kindergarten	Summer minus first grade
Fixed effects							
	Means	16.205*** (16.123,16.287)	.020*** (.012,.028)	.076*** (.054,.099)	.033*** (.024,.041)	.056*** (.030,.083)	.043** (.016,.071)
Random effects							
Child-level	Variances	2.249 ² *** (2.199 ² ,2.297 ²)	.168 ² *** (.164 ² ,.172 ²)	.420 ² *** (.409 ² ,.430 ²)	.151 ² *** (.148 ² ,.155 ²)	.148*** (.139 ² ,.156 ²)	.153*** (.144 ² ,.162 ²)
	Correlations						
		Initial BMI	-.287*** (-.317,-.258)	.240*** (.209,.272)	.152*** (.119,.186)		
		Kindergarten gain		-.433*** (-.461,-.404)	.011 (-.025,.048)		
		Summer gain			-.378*** (-.408,-.347)		
School-level	Variances	.404 ² *** (.285 ² ,.496 ²)	.051 ² *** (.042 ² ,.058 ²)	.155 ² *** (.133 ² ,.174 ²)	.059 ² *** (.051 ² ,.066 ²)	.021*** (.015,.028)	.020*** (.014,.027)
	Correlations						
		Initial BMI	-.690*** (-.884,-.495)	.252* (.009,.496)	.297* (.052,.541)		
		Kindergarten gain		-.351*** (-.526,-.176)	-.050 (-.250,.150)		
		Summer gain			-.540*** (-.674,-.405)		
Total variances		2.285 ²	.176 ²	.448 ²	.162 ²		

[^] $p < .10$, * $p < .05$, ** $p < .01$, *** $p < .001$. Parentheses enclose 95% confidence intervals.

Note. Children who attend summer school or year-round school are excluded. The “total variance” is the sum of the school- child-level variances. (The superscripted 2’s indicate squared values, not footnotes.)

Table 2. Mean differences among children with different characteristics

		Monthly BMI gain			Contrasts		
		Initial BMI	Kindergarten	Summer	First grade	Summer minus kindergarten	Summer minus first grade
Fixed effects (means and mean differences)							
Reference group (white, middle class, etc.)		16.035*** (15.857,16.213)	.008 (-.007,.024)	.065** (.025,.105)	.011 (-.004,.026)	.057* (.009,.105)	.054* (.006,.103)
Race/ethnicity	Black (vs. white)	.320** (.099,.540)	-.008 (-.027,.011)	.073** (.023,.122)	.012 (-.007,.031)	.081** (.021,.140)	.061* (.001,.121)
	Hispanic	.472*** (.263,.681)	.001 (-.016,.019)	.069** (.022,.115)	-.001 (-.019,.017)	.067* (.011,.124)	.070* (.013,.126)
	Other	-.061 (-.286,.163)	.007 (-.012,.025)	.015 (-.034,.065)	.002 (-.016,.020)	.009 (-.051,.068)	.013 (-.046,.072)
Education	Mother has not finished high school	-.102 (-.347,.143)	.015 (-.005,.036)	-.049^ (-.100,.003)	.016 (-.004,.036)	-.064* (-.126,-.003)	-.065* (-.128,-.002)
	Mother finished high school but not college	.104 (-.053,.261)	.001 (-.013,.014)	-.006 (-.038,.027)	.010 (-.002,.022)	-.006 (-.047,.034)	-.016 (-.055,.024)
Family structure	Single parent	-.022 (-.221,.178)	-.001 (-.017,.014)	-.008 (-.047,.031)	.004 (-.011,.019)	-.007 (-.055,.041)	-.012 (-.059,.035)
	Mother works	.238** (.066,.409)	.004 (-.008,.017)	-.016 (-.053,.022)	.017** (.005,.030)	-.020 (-.065,.024)	-.033 (-.078,.011)
Poverty	Household income (thousands, square root)	-.018 (-.048,.012)	-.001 (-.004,.001)	-.002 (-.008,.004)	.001 (-.001,.004)	-.001 (-.008,.007)	-.003 (-.011,.004)
Age and gender	Age at start of kindergarten (months)	.020* (.003,.038)	.002* (.000,.003)	.001 (-.003,.004)	.002*** (.001,.004)	-.001 (-.005,.003)	-.002 (-.006,.003)
	Gender (female=1)	-.215** (-.348,-.081)	.012* (.001,.023)	.012 (-.014,.039)	.003 (-.007,.014)	.000 (-.032,.033)	.009 (-.023,.041)
Random effects (residual variances)							
Total variances		2.268 ²	.175 ²	.445 ²	.162 ²		
<i>R</i> ²		.014	.003	.006	.000		

^*p*<.10, **p*<.05, ***p*<.01, ****p*<.001. Parentheses enclose 95% confidence intervals.

Note. Children who attend summer school or year-round school are excluded. The income and age variables are mean-centered. *R*² is the proportion by which the total variances have decreased from Table 1. (Not shown: child and school-level components of the total variance. Given the small *R*² values, the child- and school-level components are almost unchanged from Table 1.)