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

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Over the past 2 decades, the prevalence of overweight among young US schoolchildren has tripled, from 5% to 15% among the 6- to 11-year-old population.1-3 Overweight is especially common among young Black and Hispanic schoolchildren, approximately 20% of whom are now overweight.9 (Following conventional usage, we apply the label “overweight” to children whose body mass index [BMI] exceeds the 95th percentile on the Centers for Disease Control and Prevention’s [CDC’s] BMI-for-age charts4; these charts give the age-specific BMI distribution that prevailed before recent increases in BMI. Some researchers use the label “obese” for certain overweight children, but the word “obese” is not as clearly defined for children as it is for adults.5)

In seeking explanations for childhood overweight, some observers have pointed to schools, which 1 critic has called “obesity zones.”6,7 Schools have been faulted for serving fattening lunches,8 for scheduling inadequate time for exercise,9 and for allowing packaged-food and soft drink companies to install vending machines.10 Other observers, by contrast, have pointed to influences outside the school walls, suggesting that childhood overweight results from children overconsumption of fast food and energy-dense convenience foods,12,13 from a lack of sidewalks or recreational areas in many housing developments,14 from excessive television viewing,15 and from reductions in parental supervision as more mothers enter the workforce.16

Although each of these specific factors may have some effect, it is unclear in general whether childhood overweight arises primarily from school or nonschool influences. This issue is fundamental because it can help to focus future efforts. For example, if the major sources of overweight reside inside school walls, then interventions should focus on improving the school environment. By contrast, if the major sources of overweight are found outside of schools, then interventions that improve or compensate for the nonschool environment may be more promising.

Disentangling the effects of school and nonschool environments poses a methodological challenge. It is difficult to measure—or even to identify—all of the school and nonschool influences on body mass index (BMI). And it is both impractical and unethical to run a clinical trial in which the school “treatment” is offered to some children but withheld from others.

Fortunately, the structure of the school calendar allows us to observe children under both school and nonschool conditions. During the school year, children are exposed to a mix of school and nonschool influences, but during summer vacation they are exposed to nonschool influences alone.7,18 If overweight arises primarily from nonschool influences, we would expect accelerated BMI gains during the school year. By contrast, if overweight arises primarily from school influences, we would expect accelerated BMI gains during summer vacation.

Our main objective, then, was to compare school and nonschool influences on children’s 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). Our study design was roughly analogous to a crossover trial, in which every participant is exposed to a period of school treatment and a period of nonschool treatment. The natural experiment afforded by the school calendar, though, differs from an ideal crossover trial in 2 important ways. First, in a crossover trial, different groups would be rotated through the school treatment at different times; however, in US schools, nearly all children are exposed to the school treatment at about the same time, so the school treatment is confounded with the season of the year. Second, some children attend school during summer and thus cannot be observed outside the school environment. We excluded such children from our primary analyses, although later we discuss secondary analyses in which they were compared with other children.

METHODS

Data

To estimate school-year and summer changes in BMI, we used data from a survey...
To compensate for measurement timing, our model adjusted for the difference between each measurement date and the beginning and end of the school year. In effect, this adjustment extrapolated beyond the October and May BMI measurements to the measurements that would have been obtained had each school been visited on the first day 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:

\[ BMIm_t = \alpha_0 + \alpha_1 \text{Kindergarten}_s + \alpha_2 \text{Summer}_s + \alpha_3 \text{First Grade}_s + \epsilon_{m,t} \]

where the first component \( \gamma_0 = (\gamma_{00}, \gamma_{01}, \gamma_{02})^T \) is a fixed effect representing the grand average for the parameters \( \alpha_c \). The second component \( b = (b_1, b_2, b_3, b_4)^T \) is a random effect at the school level (level 3), representing the departure of school s from the grand average. The third component \( \alpha_c = (\alpha_{0c}, \alpha_{1c}, \alpha_{2c}, \alpha_{3c})^T \) 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 \( X_{cs} \) such as ethnicity and household income:

\[ BMIm_t = \text{Exposures}_s (\gamma_0 + \gamma_1 X_{cs} + b + \alpha_c) + \epsilon_{m,t} \]

Here \( \gamma_i \) is a matrix of fixed coefficients representing the effects of \( X_{cs} \). Equations 2 and 4 can be combined to provide a single mixed-model equation:

\[ BMIm_t = \text{Exposures}_s (\gamma_0 + \gamma_1 X_{cs} + b + \alpha_c) + \epsilon_{m,t} \]

Equation 5 shows explicitly how growth patterns are modeled with interactions between children’s characteristics (\( X_{cs} \)) and their exposures (Exposures\(_s\)) to kindergarten, summer, and first grade.

**Missing Data Strategy**

Like most surveys, the ECLS-K had a substantial number of missing values. One third of the sampled children were missing 1 or more BMI measurements, and nearly half were missing data on covariates such as income or missing dates for the beginning and end of the school year.

We filled in missing values by applying a multiple imputation strategy. Using the MI procedure in SAS version 9.1 (SAS Institute Inc, Cary, NC), we replaced each missing value with 10 random values imputed under a multivariate normal model that included all of the variables in Equation 5. (The interactions in Equation 5 were coded and imputed in the same manner as any other variable.) To account for the correlation between a child’s different BMI measurements, we formatted the data so that all of the child’s BMI measurements were grouped on a single line alongside the child’s other variables.
Although we included the dependent variable (BMI) in the imputation model, we did not use imputed BMI values in our analyses. Imputed BMIs were unnecessary because multilevel growth models do not require that every child have a measurement on each occasion. For example, if a child’s BMI was measured on 3 of the 4 measurement occasions, we used these 3 measurements in our analyses, but we did not use an imputed value for the fourth measurement. Excluding imputations of the dependent variable typically leads to better statistical estimates.

In general, multiple imputation is more efficient, and often less biased, than deletion of incomplete cases. Nevertheless, some readers may find it reassuring to know that the estimates we obtained when we deleted incomplete cases were similar to the estimates we obtained from multiple imputation.

**RESULTS**

We used the standard definition of BMI as weight in kilograms divided by height in meters squared. To aid interpretation, note that, for 5-and-a-half-year-old children of average height (1.12 m), a difference of 1 BMI unit would be a little more than a kilogram (1.12^2 = 1.25 kg).

Childhood BMI typically follows a J-shaped trajectory, falling from birth until the age of 5 or 6 years and then rising until the age of 18 years (and beyond). 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. Nevertheless, the small differences observed at this age predict larger differences later on. Five- and 6-year-old children with above-average BMIs and BMI gains are at increased risk for adult overweight.

**Average and Variance of BMI and BMI Gain**

As detailed in Table 1, average BMI growth was slower during kindergarten and first grade than during summer vacation. Children began kindergarten with an average BMI of 16.205 and then gained an average of 0.020 BMI units per month during kindergarten, 0.076 BMI units per month during summer vacation, and 0.033 BMI units per month during first grade. These average gain rates are plotted at the bottom of Figure 1. During summer vacation, average BMI growth was more than twice as fast as during either school year; the mean difference between summer and kindergarten was 0.056 BMI units per month, and the mean difference between summer and first grade was 0.043 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 nonschool environment.

Because the “average child” is not overweight, one may be less interested in average growth rate than in variation around the average. In fact, variation in BMI growth was 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 can be seen in the bottom row of Table 1, the standard deviation of BMI gain was 0.448 BMI units per month during summer vacation but only 0.176 and 0.162 BMI units per month during summer vacation, and 0.033 BMI units per month during first grade. These average gain rates are plotted at the bottom of Figure 1. During summer vacation, average BMI growth was more than twice as fast as during either school year; the mean difference between summer and kindergarten was 0.056 BMI units per month, and the mean difference between summer and first grade was 0.043 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 nonschool environment.

**TABLE 1—Gains in Body Mass Index (BMI) Among Children in Kindergarten and First Grade:**

<table>
<thead>
<tr>
<th></th>
<th>Monthly BMI Gain, kg/m²</th>
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<tr>
<td>Initial BMI, kg/m²</td>
<td>(95% CI)</td>
<td>Kindergarten (95% CI)</td>
<td>Summer (95% CI)</td>
<td>First Grade (95% CI)</td>
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<td>Fixed effects</td>
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<tr>
<td>Means</td>
<td>16.205† (16.123, 16.287)</td>
<td>0.020† (0.012, 0.028)</td>
<td>0.076† (0.054, 0.099)</td>
<td>0.033† (0.024, 0.041)</td>
<td>0.056† (0.030, 0.083)</td>
<td>0.043*** (0.016, 0.071)</td>
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<tr>
<td>Random effects: child level</td>
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<tr>
<td>Variances (SD²)</td>
<td>2.249²† (2.199², 2.297²)</td>
<td>0.168† (0.164⁴, 0.172⁴)</td>
<td>0.420²† (0.409², 0.430²)</td>
<td>0.151²† (0.148², 0.155²)</td>
<td>0.148† (0.139, 0.156)</td>
<td>0.153† (0.144, 0.162)</td>
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<td>Correlations</td>
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<tr>
<td>Initial BMI</td>
<td>-0.287† (-0.317, -0.258)</td>
<td>0.240† (0.209, 0.272)</td>
<td>0.152† (0.119, 0.186)</td>
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<tr>
<td>Kindergarten gain</td>
<td>-0.433† (-0.461, -0.404)</td>
<td>0.011 (-0.025, 0.048)</td>
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<tr>
<td>Summer gain</td>
<td>-0.373† (-0.408, -0.347)</td>
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<td>Random effects: school level</td>
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<tr>
<td>Variances (SD²)</td>
<td>0.404²† (0.285², 0.496²)</td>
<td>0.051† (0.042², 0.058²)</td>
<td>0.155²† (0.133², 0.174²)</td>
<td>0.059† (0.051², 0.066²)</td>
<td>0.021† (0.015, 0.028)</td>
<td>0.020† (0.014, 0.027)</td>
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<tr>
<td>Correlations</td>
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<tr>
<td>Initial BMI</td>
<td>-0.690† (-0.884, -0.495)</td>
<td>0.252** (0.009, 0.496)</td>
<td>0.297** (0.052, 0.541)</td>
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<tr>
<td>Kindergarten gain</td>
<td>-0.351† (-0.526, -0.176)</td>
<td>-0.050 (-0.250, 0.150)</td>
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<tr>
<td>Summer gain</td>
<td>-0.540† (-0.674, -0.405)</td>
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<tr>
<td>Total variance (SD²)</td>
<td>2.285²</td>
<td>0.176²</td>
<td>0.448²</td>
<td>0.162²</td>
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</table>

**Note:** For ease of interpretation, variances are presented as squared standard deviations; the total variance is the sum of the school- and child-level variances. This analysis excludes children who attended summer school or year-round school.

**P < .05; **P < .01; †P < .001.
during kindergarten and first grade, respectively. Disaggregating the total variance into school-level and child-level components, we found that, at both levels, the variance in summer gain significantly exceeded both the variance in kindergarten gain and the variance in first-grade gain (all \( P\)s < .001).

In addition, deceleration of BMI growth during the school year was more pronounced among overweight children than among children of normal weight. As can be seen in Table 1, at both the school and the child level, there was a negative correlation between initial BMI and BMI gain during kindergarten \((P < .001)\). This result implies that BMI growth during kindergarten tended to exhibit more rapid BMI growth than their peers during the school year and slower growth during summer vacation. Overall, our 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 assessed whether variations in BMI and BMI gain were related to the sociodemographic characteristics that past research has associated with overweight.\(^2,16,17\)

To investigate this relation, we added variables representing race and ethnicity, poverty, age, and gender to the model, as well as variables indicating the mother’s level of education and whether she worked outside the home (Table 2). Although most of these variables exhibited little relationship to seasonal BMI growth, the racial/ethnic patterns were significant and striking.

As can be seen in Figure 2, small racial/ethnic gaps were present before school began. On the first day of kindergarten, Black children were, on average, 0.320 BMI units heavier than were White children who were comparable on other variables \((P < .01)\); similarly, Hispanic children were, on average, 0.472 BMI units heavier than were comparable White children \((P < .001)\).

In addition, racial/ethnic gaps in BMI grew only during summer vacation. During this period, average monthly gains for Black and Hispanic children were 0.073 and 0.069 BMI units larger than were the gains exhibited by White children who were comparable on other variables (both \( P\)s < .01). During kindergarten and first grade, by contrast, average gains for Black, White, and Hispanic children were approximately equal.

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

**DISCUSSION**

**Limitations and Competing Explanations**

Our analyses were confined to the first 2 years of school, and it is possible that data on older children would show different patterns. In addition, given that our data were not derived from a randomized experiment, we must consider competing explanations for the effects we observed. Specifically, because exposure to the school environment is not distributed randomly across the year, it is possible that some variable other than schooling was responsible for the observed deceleration of BMI gains during the school year.

The most obvious competing explanations, however, seem relatively implausible. One such explanation is maturation. BMI growth accelerates between the ages of 5 and 7 years, \(^{24}\) so it is not surprising that BMI gains were slower during kindergarten than they were later on. Maturation, however, cannot explain the seasonal pattern of our 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 even faster growth during first grade. The observed results depart from this pattern; instead of a smooth increase, we observed an increase in BMI growth from kindergarten to summer vacation, and even faster growth during summer vacation. Maturation cannot explain why average BMI growth during the summer, it 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 also would have to increase variability in summer BMI growth and it would need to have a smaller effect on White children than on Black or Hispanic children. It is hard to imagine a confounder that would affect variability in this way. Schooling, though, can plausibly explain changes in variability. During summer vacation, every student is in a different environment, and there is tremendous variation from one nonschool environment to another. By contrast, during the school year all students are in relatively similar environments, and this similarity tends to dampen variability.28

If there were a plausible confounder, the best candidate might be seasonal variations 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.29 Again, though, this decline in summer metabolism can explain only an increase in average

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<table>
<thead>
<tr>
<th></th>
<th>Monthly BMI Gain, kg/m²</th>
<th>Contrasts, kg/m²</th>
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<tbody>
<tr>
<td></td>
<td>Fixed effects (means and mean differences)</td>
<td></td>
</tr>
<tr>
<td>Reference group</td>
<td>16.035† (15.857, 16.213)</td>
<td>0.008 (-0.007, 0.024) 0.065*** (0.025, 0.105) 0.011 (-0.004, 0.026) 0.057** (0.009, 0.105) 0.054** (0.006, 0.103)</td>
</tr>
<tr>
<td>Racial/ethnicity</td>
<td></td>
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<tr>
<td>Black</td>
<td>0.320*** (0.099, 0.540)</td>
<td>-0.008 (-0.027, 0.011) 0.073*** (0.023, 0.122) 0.012 (-0.007, 0.031) 0.081*** (0.021, 0.140) 0.061***(.001, 0.121)</td>
</tr>
<tr>
<td>Hispanic</td>
<td>0.472† (0.263, 0.681)</td>
<td>0.001 (-0.016, 0.019) 0.069*** (0.022, 0.115) -0.001 (-0.019, 0.017) 0.067** (0.011, 0.124) 0.070** (0.013, 0.126)</td>
</tr>
<tr>
<td>Other non-White</td>
<td>-0.061 (-0.286, 0.163)</td>
<td>0.007 (-0.012, 0.025) 0.015 (-0.034, 0.065) 0.002 (-0.006, 0.020) 0.009 (-0.051, 0.068) 0.013 (-0.046, 0.072)</td>
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<tr>
<td>Maternal educational level</td>
<td></td>
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<tr>
<td>Has not completed high school</td>
<td>-0.102 (-0.347, 0.143)</td>
<td>0.015 (-0.005, 0.036) -0.049 (-0.100, 0.003) 0.016 (-0.004, 0.036) -0.064** (-0.126, -0.003) -0.065** (-0.128, -0.002)</td>
</tr>
<tr>
<td>Completed high school but not college</td>
<td>0.104 (-0.053, 0.261)</td>
<td>0.001 (-0.013, 0.014) -0.006 (-0.038, 0.027) 0.010 (-0.002, 0.022) -0.006 (-0.047, 0.034) -0.016 (-0.055, 0.024)</td>
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<tr>
<td>Family structure</td>
<td></td>
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<tr>
<td>Single parent</td>
<td>-0.022 (-0.221, 0.178)</td>
<td>-0.001 (-0.017, 0.014) -0.008 (-0.047, 0.031) 0.004 (-0.011, 0.019) -0.007 (-0.055, 0.041) -0.012 (-0.059, 0.035)</td>
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<tr>
<td>Mother employed</td>
<td>0.238*** (0.066, 0.409)</td>
<td>0.004 (-0.008, 0.017) -0.016 (-0.053, 0.022) 0.017*** (0.005, 0.030) -0.020 (-0.065, 0.024) -0.033 (-0.078, 0.011)</td>
</tr>
<tr>
<td>Poverty status</td>
<td>-0.018 (-0.048, 0.012)</td>
<td>-0.001 (-0.004, 0.001) -0.002 (-0.008, 0.004) 0.001 (-0.001, 0.004) -0.001 (-0.008, 0.007) -0.003 (-0.011, 0.004)</td>
</tr>
<tr>
<td>Age at start of kindergarten, mo</td>
<td>0.020* (0.063, 0.038)</td>
<td>0.002** (0.000, 0.008) 0.001 (-0.003, 0.004) 0.002† (0.000, 0.004) -0.001 (-0.005, 0.003) -0.002 (-0.006, 0.003)</td>
</tr>
<tr>
<td>Gender (girl = 1)</td>
<td>-0.215*** (-0.348, -0.081)</td>
<td>0.032** (0.001, 0.023) 0.012 (-0.014, 0.039) 0.003 (-0.007, 0.014) 0.000 (-0.032, 0.033) 0.009 (-0.023, 0.041)</td>
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</table>

| Total variances, SD²         | 2.268²                     | 0.175²                  | 0.449²                  | 0.162²                  |
| R²                          | 0.014                       | 0.003                   | 0.006                   | 0.000                   |

Note. For ease of interpretation, variances are presented as squared standard deviations. The total variance is the sum of the school- and child-level variances, and the R² value represents the proportion by which the total variance has decreased from the total variance shown in Table 1. The reference group consists of White boys of average age and median family income whose parents are cohabiting high school dropouts. 

aVersus White. 
bSquare root of household income in thousands. 

P <.10; **P <.05; ***P <.01; †P <.001.
BMI growth; it cannot explain the observed increase in the variability of BMI growth. In addition, a metabolic explanation fails to account for the weight-gain patterns of adults, who gain weight fastest not during the summer, when their metabolisms are slowest, but during the winter holidays.30

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

**Remaining Questions**

Like any research, this study raises questions that the data cannot fully answer. For example, do children tend to gain BMI more rapidly during summer vacation? Do children eat more in the summer? Do they exercise less? Unfortunately, the survey we used (ECLS-K) sheds little light on these questions. Although consumption and exercise were measured, the measures were very crude and were not applied in a consistent manner across seasons.

During the school year, for example, the survey provided information on which children ate school lunches and how many hours children spent in physical education class; by contrast, during the summer the survey provided data on which children ate dinner with their families and which children participated in organized sports. It is impossible with this information alone to make informative comparisons between summer and school-year patterns of exercise and eating. (A different study suggested that children consume about the same amount of food energy during the summer and the school year,31 but that study was based on self-reported data, which tend to lead to underestimates of overeating.32)

Another question is whether particular school policies are responsible for reducing BMI growth. This question was beyond the scope of our study, which set out to detect differences between school and nonschool environments rather than differences in policies between one school and another. However, a previous study in which a different design was used to study the same data suggested that increasing hours of physical education could reduce BMI gain among overweight girls.33

A final question is whether summer BMI growth would be reduced if children spent the summer in a school environment. On this question, the ECLS-K does provide some evidence, though not enough to answer the question with confidence. Eleven percent of the surveyed children attended summer school, but only 1% were enrolled in summer school for more than half of the usual summer vacation. In addition, only 3% of the children attended year-round schools.

In supplemental analyses, we compared the small number of children who attended year-round school or summer school against children who had spent the summer on vacation (with control for the other variables in Table 2). The results were ambiguous. During summer, the estimated effect of attending year-round school was −0.201 BMI units per month (P<.01; 95% confidence interval [CI]=−0.348, –0.065), whereas the estimated effect of attending summer school was only −0.005 BMI units per month (P=.9; 95% CI=−0.102, 0.092). Both point estimates were negative, as expected, but only 1 was significantly different from zero, and both confidence intervals were quite wide, indicating substantial uncertainty about the true effect of attending school during summer.

**Conclusions**

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

How do schools inhibit BMI growth? Although our data cannot answer this question directly, we conjecture that the structured nature of the school day, with its scheduled exercise periods and limited opportunities to eat, helps students 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 and why adults gain weight faster during the winter holidays than at other times of year.

These patterns have important implications for policy researchers interested in reducing childhood overweight. A negative implication is that interventions that focus exclusively on improving unhealthy aspects of the school environment—for example, removing soft drink vending machines—may have limited effects given that the major sources of overweight reside outside the school walls. A more positive implication is that policies that increase children’s exposure to school environments (e.g., after-school programs or longer school years) may have the potential to reduce childhood overweight.

The finding that overweight comes mainly from nonschool sources does not mean that school-based interventions are doomed to failure. Rather, it suggests that policies that merely improve the school environment may be less effective than are policies that improve or compensate for unhealthy nonschool behaviors. Lessons on nutrition, for example, may improve children’s out-of-school eating habits, particularly if parents are involved.

Likewise, physical education courses may be most beneficial for children whose out-of-school activities are sedentary. In short, perhaps the most productive interventions will be those that target children’s behavior not only during school hours but also and most important, after the bell rings.

Acknowledgments
This project was supported by the American Educational Research Association, the Spencer Foundation, and the National Science Foundation (grant SES-98112267). We thank Sharon Balter, Chris Browning, R.D. Fulk, Kathryn Lively, Maureen Tobin, Pete von Hippel, and Kristi Williams for comments on earlier versions of the article.

Human Participant Protection
No protocol approval was needed for this study.

References

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This article was accepted June 12, 2006.

Contributors
P.T. von Hippel conducted the analyses and led the writing. B. Powell shared in the writing, framing, and interpretation. D.B. Downey originated the study and shared in the writing, framing, and interpretation. N.J. Rowland led the literature review.