PEER-EFFECTS ON CHILDHOOD OBESITY

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Peer-Effects on Childhood Obesity

ABSTRACT

This study investigates whether peers are a contributing factor in the increase in childhood obesity rates, and whether peer effects vary by race, gender and residential neighborhood. We control for the commercial food environment around schools and residence when estimating peer effects given that the food environment constitutes an important set of factors that have not been adequately measured and accounted for in previous studies. We find that the weight of peers within the same grade in a school significantly impacts body mass index (BMI) z-score of an individual student. A typical student’s BMI z-score increases when facing heavier peers and it decreases when facing lighter peers. The results show differential peer-effects across race and gender, but more so by gender than by race.
INTRODUCTION

There is growing evidence that individuals in a network can significantly influence the behavior of one another. Consequently, peer effects in health behaviors are of interest to researchers and policy makers because their existence raises the possibility of gaining greater benefits from health interventions via a social multiplier effect. Peer groups may support and/or reinforce the determination to attain or maintain healthy weight, and also complement various interventions aimed at improving health behaviors (Christakis and Fowler, 2007; Halliday and Kwak, 2009; Carrell, Hoekstra and West, 2011). Most of the research on peer effects, however, focused on substance-abuse and other health behaviors. In these areas, the research has more convincingly demonstrated the existence of peer-effects. For example, Botvin et al. (1984) found peer-influences on substance-abuse. Clarke et al. (1986) found that peers could reduce the behavioral intention to smoke cigarettes. Using an instrumental variables approach, Fletcher (2012) also identified peer effects in alcohol use.

Peer effects on obesity have only recently received attention. One of the earliest studies to find statistically significant effects of friends in a network was undertaken by Christakis and Fowler (2007) (CF) who found that there is a 71% odds (ratio) that an individual would become obese if his or her friend becomes obese. Although their findings are robust to different specifications and occurs significantly only in the direction of friendship, Cohen-Cole and Fletcher (2008) criticized their model for not including environmental attributes or correlated factors that can bias the peer-effects estimate. Using different data, Cohen-Cole and Fletcher (2008) (CCF) also observed a similar increase as reported by CF without the inclusion of the environmental attributes. However, after they included the environmental attributes in their model, the estimates decreased from 0.05 to 0.037, a 30% decrease. Further, after including
individual fixed effects, their estimate was no longer statistically different from zero. In another study, Trogdon, Nonnemaker, and Pais (2008), using an instrumental variables approach, found a 0.39 probability of becoming overweight in response to a unit increase in the proportion of friends becoming overweight.

Yakusheva, Kapinos, and Weiss (2011) argue that the above studies suffer from several biases; the CCF study does not address reflection bias, while Trogdon, Nonnemaker and Pais (2008) do not address self-selection. Using random assignment of roommates in a college dorm for female students as a source of identification, Yakusheva, Kapinos and Weiss (2011) find positive peer-effects on dietary and exercise behavior among roommates through the freshman year. They, however, do not show any direct evidence of weight changes arising from interactions among roommates through the freshman year.

An important point to note is that all of the above studies of peer influence on obesity focused on adults or adolescents. While adolescence is a stage when peers make a big impact, pre-adolescence is a good stage to inculcate healthier lifestyles (Kelder et al, 1994). In other words, interventions focused on young children, such as those in elementary schools where students are beginning to learn and absorb behavior related to diet and physical activity, could be most effective at preventing future occurrences of obesity. To the extent that peer effects are important in elementary schools, an understanding of these effects may aid in the design of programming to promote health among children. In addition, with the exception of the Yakusheva, Kapinos, and Weiss (2011), the existing literature on peer effects on obesity has generally not fully addressed several challenges in identifying peer effects (Halliday and Kwak, 2009). To address these voids, we focus on elementary school children and investigate if peers are a contributing factor in the increase in childhood obesity rates.
Our study contributes to the literature on peer-effects and obesity in several ways. One, we exploit the exogenous assignment of students to schools, and thereby peers, affecting several tens of thousands of students in elementary schools. Two, this study is the first to analyze peer influence among elementary school children, an important stage when habits are malleable. Three, we control for the commercial food environment, including restaurants and grocery stores, around schools and residences with precise geographic data. These constitute correlated factors that could simultaneously influence food consumption among all students in a grade within a school. These factors have been largely ignored in previous literature on peer-effects on obesity. Four, in contrast to several past studies, the BMI data we use are measured by trained personnel, as opposed to being self-reported. In our analysis, we include various sets of contextual and correlated factors that typically bias peer-effects.

This article also differs from previous studies on peer-effects and obesity in terms of definition of peers. Previous studies on peer-effects on obesity focus on the influence of friends’ within a network (for example, CF and CCF). While social network plays an important role in friend’s behavior, a school setting provides a unique environment where individuals can interact on most weekdays during a school year in a variety of ways that could influence food consumption and physical activity.

We follow the same definition adopted in the education literature generally, which defines peers at a grade-level within a school (Hoxby, 2000). The student and peers all interact and spend time in the same environment, and a classroom provides a unique environment where the shared goal is that of academic progress. Peers within a class or grade almost always have common schedules for meals and physical activities. As discussed in Asirvatham, Nayga, and Thomsen (2013), studying peer-effects within a school has some practical advantages.
Identifying peer groups outside of school can take a great deal of effort, and social networks may not be stable over time. In contrast, classroom peers are relatively more stable, and if peer-effects are significant and sizeable, such effects should be taken into consideration while designing effective school-level policies and programs targeting childhood obesity related issues.

In this study, we estimate the change in the BMI z-score of a student in response to a change in the proportion of obese peer students, ceteris paribus. The peers are defined as all other students in the same grade within a school. One objective of this study is to estimate peer effects in general, and the other is to examine if peer effects vary by race, gender, and residential neighborhood. Shedding more light on the difference in peer-influences by race and gender is especially important because obesity prevalence and rates of obesity increase vary by ethnic or racial group and by gender (Baskin, Ahluwalia, and Resnicow, 2001; Wang and Beydoun, 2007).

Our analytical methods address omitted variable and self-selection biases, and we try to separate the peer-effects from peers by race, gender and residential neighbors. Despite the variety of specifications and methods used, the reflection bias can still exist. Reflection bias remains in the peers’ variable because a student can influence peer(s) and could in turn be influenced by peer(s), even if they are randomly assigned. We partly address this by including obese proportion among student peers in other grades but within the same school.

Our results show a little over one-third standard deviation increase in body mass index (BMI) in response to a doubling of the proportion of obese students among peers in the same grade within a school. In a nutshell, we find that peer-effects are robust to alternative specifications, and that these effects differ by race and gender.

DATA
The data that we used in our analysis are from the state of Arkansas. Arkansas is an interesting state to study because it has a high rate of childhood obesity and is one of the first states to require BMI measurements of public schoolchildren. Beginning in the 2003-2004 school year, Arkansas law has required that public schoolchildren be assessed for BMI. Height and weight measurements are taken in the schools and reported to the Arkansas State Department of Education (ADE). The BMI z-scores along with data on race, gender and participation in free or reduced lunches are housed at the Arkansas Center for Health Improvement (ACHI). The fact that our data are based on actual weight and height measurements is one important advantage of the BMI z-scores used here. Our focus is on the subset of BMI records that apply to elementary schoolchildren. Given the panel data methods used in this study, only those students with at least three observations are included in our analysis samples. Throughout this study, we categorize students into four mutually exclusive categories. A child is considered obese if he or she falls at or above the 95th percentile on the CDC reference growth chart. Children are considered overweight if they if at or above the 85th but below the 95th percentile. Children are classified as normal weight if they are between the 5th and 85th percentiles. Finally, a child is considered underweight if at or below the 5th percentile.

A second source of data we bring into the analysis reflects the commercial food environment around schools and residences. Business data on the geographic locations of restaurants, grocers, and other food stores was obtained from Dun & Bradstreet. Details on the construction of the food environment are provided in Appendix A. These data were matched geographically to the locations of schools and student residences. Measures around schools reflect varying radial distances from schools in the increments of a third of a mile up to a mile, and these include the number of 1) fast food restaurants and sandwich places and 2) pizzerias.
Variables around a student’s residence include distance to the nearest 1) grocery store, 2) dollar store, 3) convenience store, 4) fast food restaurant, 5) pizzeria, and 6) sandwich place.

Our empirics are based on a panel dataset covering the years 2004 to 2010. One problem we confronted in assembling the data set is that state policy relating to the frequency of BMI measurement changed during our study period. From 2004 to 2007, the BMI of school children were measured annually for grades K - 12. Thereafter, BMI was measured and reported only for children in even grades through the 10th grade (K, 2, 4, 6, 8 & 10). Thus, we have BMI prevalence rates for all grades from 2004 through 2007, but only for even grades after 2007. The non-reporting of obesity prevalence in odd grades after 2007 should not bias our estimates, since the decision to stop measuring the BMI of children in odd-numbered grades was exogenous in that it was not made by the child, the child’s family, or the child’s school. However, this change in reporting does affect our ability to take into account BMI changes in a consistent fashion over time.

METHODS

Our model is based on Manski’s (1993) basic peer effects model in a panel framework, and is written as follows:

\[ Y_{igkt} = \beta_0 + \beta_1 Y_{igkt} + \beta_2 X_{igkt} + \beta_3 X_{-igkt} + \beta_4 Z_{kt} + \beta_5 Z_{-it} + U_{ikt}, \]  

where \( Y_{igkt} \) is the BMI z-score of the \( i \)th student in grade \( g \) of school \( k \) at time \( t \); \( Y_{igkt} \) is a vector of peer-student proportions in three mutually exclusive weight categories (underweight, overweight and obese). Specifically these represent the proportions of students other than student \( i \) in the same grade \( g \) in the same school \( k \) at time \( t \); \( X_{igkt} \) is a vector of student \( i \)’s characteristics; \( X_{-igkt} \) is a vector depicting averages of peer characteristics in grade \( g \) other than student \( i \); \( Z_{kt} \) is a vector
of observed factors at school $k$, which includes food environment; $Z_{it}$ is the vector of commercial food environment around the residence of student $i$; and $U_i$ is the error term which equals $\mu_i + \varepsilon_{it}$, where $\mu_i$ is the unobserved time invariant component and $\varepsilon_{it}$ is the spherical error term.

Following Manski’s terminology, $\beta_1$ represents the endogenous peer effects. The three mutually exclusive weight categories (i.e., underweight, overweight and obese) are introduced into the model to test if heavier peers have an increasing effect and lighter peers a decreasing effect in a monotone fashion. Even though many elementary schools in Arkansas are large enough to require multiple classrooms for students in single grade, the grade within an elementary school is the ideal level to represent the peer effects. Students in the same grade generally share common recess and lunch times.

In addition, given that race has both social and economic connotations, we examine how race plays a role in peer effects. In our sample there are relatively small numbers of Asian and Native American students in many schools and schools with substantial proportions in these racial categories are unevenly distributed across state$^1$. For this reason, we focus primarily on the larger Caucasian, African American and Hispanic categories. There are two ways by which we evaluate the role of race in the context of peer-effect: 1) to see whether the race of a student makes him/her more affected by peers’ obese or overweight composition; 2) to see whether a particular racial peer group exerts larger influence. To answer the first question, we interact the proportion of obese students with the race of the $i^{th}$ student. So the specification is now,

$$Y_{igt} = \beta_0 + \beta_1 Y_{-igt(r)} + \beta_2 X_{igt} + \beta_3 X_{-igt} + \beta_4 Z_{kt} + \beta_5 Z_{it} + U_{ikt}$$

All variables are the same as in equation (1) except for $Y_{-igt(r)}$, which is now a vector of obese student proportions under different race categories indicated by ‘r’. To answer the second

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$^1$ To put more light in this issue, it is worth pointing out that 50% of schools have no Asian students, and only about 25% have 1% or more Asian students. From the available information, the highest Asian student percent was 26% in one school in 2009; and the school at the 99th percentile when ranked by proportion of Asian students was at 13%.
question, we separate proportion of peers under different weight categories by race. So, for example, there is an obese proportion, one for each race.

Peer effects could also vary due to gender composition of obese peers, since persons of different gender could view their peers differently. For example, girls are more body image conscious than are boys (Wood, Becker and Thompson, 1996). Surprisingly, this has been observed even among elementary schools. For example, Vander Wal and Thelen (2000) and Frost and McKelvie (2004) report that body image problems are spilling over to dietary choices as early as lower elementary school students. Wood, Becker and Thompson (1996, p. 85) reported that “girls demonstrated significantly higher levels of body dissatisfaction and lower levels of self-esteem than boys.” In general, boys are more physically oriented than girls, and also interact with peers differently with male peers and female peers (Markovits et al., 2001; Wilkinson and Fung, 2002; Phares et al., 2004; Bailey, Wellard and Dismore, 2005). In the case of the analysis by gender, $Y_{igkt(r)}$ in equation (2) is changed to include two gender types, while everything else remains the same in the model.

Finally, we examine whether peers from the same neighborhood have a differential effect. We define neighborhood peers as other students in the same grade in the same school who live in the same census block group. We included this analysis since children tend to also have opportunities for interaction outside of school hours. The interest here is to put more light on peer influences within the same grade, and therefore, we include only those peers in the same grade living in the same neighborhood.

Some studies have also found that students across grade might also influence one another’s behavior, especially with regard to diet and physical activity. Leatherdale and Papadakis (2011) and Asirvatham, Nayga, and Thomsen (2013) show evidence of older graders
impacting younger graders within a school. We look into specifications that include obesity prevalence rates among students in other grades within the same school to capture their influence as well. However, due to multifarious grade configurations among elementary schools in Arkansas, understanding such peer influences across grades requires a more detailed investigation, which is beyond the scope of this article. Moreover, estimating and understanding peer-effects within a grade is central to this paper, particularly because own grade is where students interact most.

The panel nature of the data and the amount of information on students, schools and food environment allows us to control for individual and peer characteristics that reduces the bias of the endogenous peer estimate. The bias occurs because these factors could simultaneously influence all graders within a school.

Even though we control for several student and peer characteristics, environmental features, and other observables, our analysis do not fully eliminate all potential biases due to the presence of unobservable factors that could be correlated with outcomes of peers. For example, not controlling for some characteristics, such as parental education and income, could potentially bias the estimates. Better education of parents, for example, is correlated with lower prevalence of obesity (Greenlund et al., 1996; Chen, Martin and Matthews, 2006). There are also unobserved factors that might increase obesity prevalence among younger grades such as the availability of vending machines with unhealthful food products or other unhealthful environmental features. These, on the one hand, might increase obesity prevalence in a grade. On the other hand, there could be factors that might counter the increase in obesity prevalence, such as programs that increase physical activity levels or those that create an environment for more healthful choices.

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2 A study by Asirvatham, Nayga, and Thomsen (2013) discusses more on this issue.
In addition to the school environmental features, parental school choice could also affect child health outcomes, as has been noted in the academic performance literature (Bauch and Goldring 1995). The evidence on parents choosing the school for their child based on healthful environment, however, is lacking. Furthermore, most public schools admit local students, and admit children from other areas only if space is available and an open enrollment policy is in place. Thus, we do not expect much of the influence of school-choice related omitted variable(s) in the model.

To control for time invariant unobservables, we employ fixed effects models. One-way FE models account for bias in the peer-effect estimate due to its correlation with the time invariant unobserved component. Since there could be year-to-year changes in the BMI that if not accounted for might bias the regressors, we also estimate a two-way FE model by adding binary variables for different years. Our analytical methods, however, do not address bias due to time varying unobservables.

RESULTS

Table 1 presents peer effect estimates for different weight proportions. All regressions control for the food environment around the child’s residence. Table 1 includes results from pooled OLS, one-way FE without school-level food environment measures, two-way FE without school-level food environment measures, and two-way FE with school-level food environment measures. The school-level food environment is presented in a separate regression because sheds light on the impact of a characteristic that is shared among all the peers. A comparison across estimates of the different peer-weight categories in Table 1 reveals that the peer effect monotonically increases according to the proportion of peers in increasingly heavy body-weight
classifications. In addition, the effect of obese peers is significantly higher than that of overweight peers.

The pooled OLS estimates for the obese category presented in Table 1 suggest a nearly one standard deviation increase in response to a twofold increase in the obese proportion among peers in the same grade. Interestingly, the random effects estimate is nearly half that of the OLS estimate. In the fixed effects models, the estimate for the obese category drops another 20% to around 0.40. Thus, there is clear evidence that individual effects matter. The similarity between the random effects and fixed effects estimates suggest that the bias resulting from the correlation between individual time invariant factors and peers’ weight is relatively small. The inclusion of year binaries to the fixed effects model does not meaningfully change the estimate nor does the inclusion of additional controls for the food environment around schools. In other words, we find no gain in efficiency in the FE models by accounting for the food environment around schools once the food environment around residence and other correlated and contextual factors are accounted for. This could suggest that what we observe is close to the true peer-effect. In what follows, all models include binaries for year and controls for food environment around both the residence and school of the child.

**Peer effects and race**

Table 2 presents estimates of the peer effect with the obese proportion interacted with the student’s own race. These estimates can be used to examine if peer-effects vary by the student race. Results from the two-way fixed effects suggest that African Americans are the most responsive to the body weight of peers followed by Hispanics and then by Caucasians. Aside from this finding, it is worth pointing out differences across models by race. The pooled OLS
results show that the z-scores of Caucasian students increase by one standard deviation in response to a doubling of proportion of obese peers. Again, the magnitude of the random effects estimate for Caucasian students is less than half (56%); and the fixed effects estimate is about 20% smaller still. The estimates for African Americans and Hispanics are quite different. The random effects estimates for African Americans and Hispanics are only 10% and 22% lower, respectively, than the pooled OLS estimates. Moreover, the two-way FE estimates for both African Americans and Hispanics are not statistically different from the random effects estimates. Thus we do not observe the same significant correlation between the unobserved factors and the peer-effect for these two racial categories.

The above regression results showed that peer effects can vary depending on the race of the student. A natural follow-up question is whether peer influence varies depending on obesity prevalence among peers of one’s own race and peers of other races. Results presented in Table 3 indicate that obese proportion among peers of one’s own race matter marginally less than the percentage of obese students of other races; although the difference is not statistically significant. This relative magnitude between the own and other-race peer effect remains consistent regardless of the estimation method employed. Taken together, findings in Table 2 and 3 suggest that the race of the obese peers do not matter, but the race of the student does matter.

**Peer effects and gender**

Table 4 presents peer effect estimates obtained by interacting the student’s own gender with the proportion of students under the different weight categories. Pooled OLS estimates indicate that doubling of the percent of obese girls is associated with nearly a one standard deviation (0.97) increase in the BMI z-score. The coefficient for boys is 0.15 standard deviations smaller at 0.82.
However, the effect of overweight peers is actually higher for boys than for girls at 0.58 and 0.53 standard deviations, respectively. As before, the random-effects model shows reduced magnitudes of the effect of obese peers (by at least 42%). The fixed-effects estimate is about 20% lower than the random effects estimate regardless of gender. Furthermore, the difference in obese peer effects between genders becomes insignificant in the fixed effects model but this difference remains significant in the overweight peer effects.

Next we ask whether the proportion of obese students of one’s own gender matters more than the proportion of obese students of another gender. Results presented in Table 5 suggest that own-gender peers do matter more. In the OLS model, the own-gender peer effect is 0.25 standard deviations larger than the effect of peers of the other gender. As before, magnitudes of both own-gender and other-gender peer effects decline in the fixed and random effects models, but the difference between own-gender and other-gender peers remains statistically significant.

**Peer effects among neighboring students**

Other than race and gender, peer groups could also be affected by proximity to residence. As discussed in the methods section, the interest here is to broaden the understanding of peer influences within the same grade, and therefore, we include only those peers in the same grade living in the same census block group. Those in the same grade in the same school but not in the same census block group are grouped into the ‘other’ category. If neighboring students show larger peer-effects, then it would be easier to identify groups for implementation of intervention programs. The two-way FE results presented in Table 6 indicate that the magnitude of the estimate of peers in the same census block group is 0.33 and that of others outside of the census
block group is 0.39. The difference, however, are not significant. Thus we do not see any statistical difference in peer-effects by neighborhood of residence.

Comment on Alternative specifications

The peer-effect is endogenous in that it represents the outcome of people interacting with one another. Therefore, a natural consequence of modeling the peer environment is that many of the shared variables exhibit high collinearity. Because of this, we estimate alternative specifications, beyond those by race, gender, and neighborhood. We specifically control for peer characteristics in terms of participation in the free or reduced lunch program and obesity prevalence among students in other grades but in the same school.

Results (not reported) indicate that the findings presented above are robust to these alternative model specifications. The effect of the peers in other grades within the same school, however, was significant and positive but only two-thirds the size of the own grade peer effect. This is consistent with existing evidence in the literature on, say, older graders influencing younger graders in the same school (Asirvatham, Nayga and Thomsen, 2013) and indicates that there is indeed across grade influence but that this influence is much smaller than the effect of own-grade peers. It also shows that own-grade peer effects are in addition to the effects of peers from other grades in the same school.

CONCLUSIONS

This study was conducted to analyze peer-effects among elementary students in public schools, and further examine if peer influence varies by race, gender and proximity to residence. The latter questions are more than academic exercises, as they evaluate whether a student of a
particular race or gender is relatively more vulnerable to peer influence, and if a specific race or
gender exerts more influence. Existing literature shows mixed findings ranging from no effect to
some significant effects. This might be due to different sets of information being used across
studies.

We compare models that include different sets of contextual and correlated factors that
typically bias peer-effects. We place more confidence in the peer-effects estimates from the two-
way fixed effects models, which control for the individual student-level unobserved factors, and
also control for the commercial food environment around schools and residence. Using unique
geographic data, we account for the commercial food environment around schools and residence.
These are correlated factors that could simultaneously influence all peers. Common
environmental features, such as the commercial food environment, could upward bias the
estimate, since it affects all members in the peer group. However, accounting for the commercial
food environment around schools reduced the estimate but only marginally and the reduction
was not statistically significant. Overall, the results show consistent peer-effects within
elementary school grades. The estimates are smaller in magnitude after including more factors.
It is important to account for time-invariant, unobserved factors. This is shown by the large
reduction in the magnitude of the peer effect that comes from use of a panel data estimator and
provides evidence that unobserved student-level factors positively bias the pooled OLS estimates
by a substantial degree.

Alternative specifications to address the endogenous outcome among peers suggest that
peer characteristics and even obesity prevalence among students in the rest of the school might
not bias the peer-effects estimates much. The estimate of peers within a grade is much larger
than peers in other grades within the school. This also suggests that peers in the rest of school
matter but not as much as peers within a grade. The peer-effects estimate (of own grade) with and without obese student proportion in other grades changes only marginally. Such minimal changes in the own-grade estimate might suggest that obese peers among other grades have an additive effect to that found for own-grade peers.

We find evidence that peer-effects differed based on race and gender. Every doubling in the proportion of obese students within the same grade increased the student’s BMI by 0.42 standard deviations. On racial peers, the standard deviation increase is in the order: 0.55 if the student was Hispanic, 0.48 if African American, and 0.33 if the student was a Caucasian. Although not definitive, this might help in understanding why African Americans have seen relatively higher increases in obesity rates in the recent decades (Baskin, Ahluwalia and Resnicow, 2001). Gender also seems to matter because the peer effect for female students was nearly 0.70 standard deviations while the increase for male students was 0.50 standard deviations. In sum, our findings suggest it would be important to incorporate demographic dimensions into the design of school-level policies to reduce obesity.

In this study, although we control for food environment around schools and residence, there could be difference in the food environment within schools. Such differences could be because of different policies towards menus, vending machines, etc. (Raczynski et al., 2009). Such school characteristics, to the extent they vary with time, affect student choices and the fixed effects methods only partly address this issue. Some biases due to the presence of time varying unobserved factors might still remain.

In summary, we address several of the biases that typically plague peer-effects studies by using different estimation methods, including student fixed effects to estimate peer effects. Our results are quite robust across these estimation methods despite data limitations. An interesting
observation in our results is that once we account for individual heterogeneity and include year fixed effects in the model, the estimates become robust to alternative specifications.
REFERENCES


Table 1: Impact of proportion of underweight, overweight, and obese peers on BMI Z-score

<table>
<thead>
<tr>
<th>Peer proportion</th>
<th>OLS</th>
<th>Panel Methods</th>
<th></th>
<th></th>
<th></th>
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<tbody>
<tr>
<td></td>
<td></td>
<td>Random-Effects</td>
<td>One-way FE</td>
<td>Two-way FE</td>
<td>Two-way FE with Food Environment</td>
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<td>Underweight</td>
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<td></td>
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<td>(0.01)</td>
<td>(0.01)</td>
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</tbody>
</table>

Note: Regressors in each regression model include student age, race, gender, rural/urban area of residence, participation in school free/reduced lunch program, and food environment around residence. The one-way fixed effects (FE) model includes student fixed effects; and the 2-way FE model includes year dummy variables in addition to the student fixed effects. “Food Environment” stands for the commercial food environment around schools. Standard errors are in parentheses.
<table>
<thead>
<tr>
<th>Race categories</th>
<th>OLS</th>
<th>Random-Effects</th>
<th>Two-way FE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Caucasian</td>
<td>1.01</td>
<td>0.44</td>
<td>0.34</td>
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<td></td>
<td>(0.03)</td>
<td>(0.02)</td>
<td>(0.02)</td>
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<tr>
<td>African American</td>
<td>0.55</td>
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</tbody>
</table>

Note: Regressors in each regression model include student age, race, gender, rural/urban area of residence, participation in school free/reduced lunch program, year dummies, and food environment around each student’s residence and around school. The two-way FE model includes year dummy variables in addition to the student fixed effects. Standard errors are in parentheses.
<table>
<thead>
<tr>
<th>Race</th>
<th>OLS</th>
<th>Random-Effects</th>
<th>Two-way FE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Own</td>
<td>0.97</td>
<td>0.47</td>
<td>0.36</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Other</td>
<td>1.04</td>
<td>0.52</td>
<td>0.42</td>
</tr>
<tr>
<td></td>
<td>(0.04)</td>
<td>(0.03)</td>
<td>(0.03)</td>
</tr>
</tbody>
</table>

Note: Regressors in each regression model include student age, race, gender, rural/urban area of residence, participation in school free/reduced lunch program, year dummies, and food environment around each student’s residence and around school. The two-way FE model includes year dummy variables in addition to the student fixed effects. Standard errors are in parentheses.
### Table 4: Impact of proportion of underweight, overweight, and obese peers across gender on BMI Z-score

<table>
<thead>
<tr>
<th>Peer proportion</th>
<th>Gender</th>
<th>OLS</th>
<th>Random-Effects</th>
<th>Two-way FE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Underweight</td>
<td>Male</td>
<td>-1.13</td>
<td>-1.41</td>
<td>-1.45</td>
</tr>
<tr>
<td></td>
<td>Female</td>
<td>-1.50</td>
<td>-1.49</td>
<td>-1.51</td>
</tr>
<tr>
<td>Overweight</td>
<td>Male</td>
<td>0.58</td>
<td>0.40</td>
<td>0.37</td>
</tr>
<tr>
<td></td>
<td>Female</td>
<td>0.53</td>
<td>0.38</td>
<td>0.34</td>
</tr>
<tr>
<td>Obese</td>
<td>Male</td>
<td>0.82</td>
<td>0.47</td>
<td>0.40</td>
</tr>
<tr>
<td></td>
<td>Female</td>
<td>0.97</td>
<td>0.48</td>
<td>0.39</td>
</tr>
</tbody>
</table>

Note: Regressors in each regression model include student age, race, gender, rural/urban area of residence, participation in school free/reduced lunch program, year dummies, and food environment around each student’s residence and around school. The two-way FE model includes year dummy variables in addition to the student fixed effects. Standard errors are in parentheses.
Table 5: Impact of proportion of obese peers of own gender and the other gender on BMI Z-score

<table>
<thead>
<tr>
<th>Gender</th>
<th>OLS</th>
<th>Random-Effects</th>
<th>Two-way FE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Own</td>
<td>0.86</td>
<td>0.4</td>
<td>0.33</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Other</td>
<td>0.61</td>
<td>0.31</td>
<td>0.26</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
</tbody>
</table>

Note: Regressors in each regression model include student age, race, gender, rural/urban area of residence, participation in school free/reduced lunch program, year dummies, and food environment around each student’s residence and around school. The two-way FE model includes year dummy variables in addition to the student fixed effects. Standard errors are in parentheses.
<table>
<thead>
<tr>
<th>Census block group*</th>
<th>OLS</th>
<th>Random-Effects</th>
<th>Two-way FE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Own</td>
<td>0.97</td>
<td>0.44</td>
<td>0.33</td>
</tr>
<tr>
<td></td>
<td>(0.05)</td>
<td>(0.03)</td>
<td>(0.03)</td>
</tr>
<tr>
<td>Other</td>
<td>0.99</td>
<td>0.49</td>
<td>0.39</td>
</tr>
<tr>
<td></td>
<td>(0.03)</td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
</tbody>
</table>

Note: Regressors in each regression model include student age, race, gender, rural/urban area of residence, participation in school free/reduced lunch program, year dummies, and food environment around each student’s residence and around school. The two-way FE model includes year dummy variables in addition to the student fixed effects. Standard errors are in parentheses.

* Own represents those students in the same grade in the same school and in the same census block group; and Other includes students in the same grade in the same school but not in the same census block group.
COMMERCIAL FOOD ENVIRONMENT MEASURES

Data on the commercial food environment were acquired from Dun and Bradstreet (D&B). These data contain the name, address, geographic coordinates, business type, and in some cases, a measure of total sales and number of employees. Archival D&B data were purchased so that there is a picture of the food landscape during each year for which BMI measures are available. These data reflect establishment counts as of December of the year in question. We worked with D&B to assure that the establishment covered in the dataset covered the major sources of calories in the commercial environment. Consequently, our dataset includes establishment classified as drugstores, variety (dollar) stores, and includes discount retailers (non-supercenter formats for companies like Walmart, Target, and K-mart that often carry limited range of food items).

Food stores were classified into larger grocery stores, discount retailers with a narrow selection of foods, dollar stores, convenience stores, and specialty food retailers. The logic of the classification scheme is to capture both the selection of foods available for sale and also the price points across the different formats. Restaurants were classified as full-service restaurants, fast food restaurants, sandwich shops (e.g., Subway), pizza places, coffee houses (e.g., Starbucks), and specialty food-away-from-home outlets (e.g., ice cream parlors).

In this study we use only select variables. Variables around a student’s residence include distance to the 1) nearest grocery store, 2) dollar store, 3) convenience store, 4) fast food restaurant, 5) pizzeria, and 6) sandwich place. Variables around the school are measured at
varying radial distances from schools in the increments of a third of a mile, and these include the number of 1) fast food restaurants and sandwich places and 2) pizzerias.

There were a relatively high proportion of errors in SIC codes provided for establishments in the D&B data. For this reason, classification of food stores and restaurants was based on several strategies. Chain stores and restaurants could often be classified by parent company or by franchise name. In other cases, establishments were classified by keywords contained in the company name or trade description and SIC code. When there were questions as to the type of establishment, research assistants verified store existence through street-view images of the Google search engine or via telephone call to the number contained in the D&B database.