PEER-EFFECTS ON CHILDHOOD OBESITY: AN INSTRUMENTAL VARIABLES APPROACH ON EXOGENOUSLY ASSIGNED PEERS

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This study investigates whether peers are a contributing factor in childhood body-weight outcomes. Using an instrumental variables method on exogenously assigned peers, we find that the weight of peers within the same grade and 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. The size of the peer-effect, however, is very modest. For a percentage point increase in the proportion of obese students in the same grade, a typical student's BMI z-score increases by only 0.00341 standard deviations.

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Peers are an important source of influence on health behaviors. Arguably, much of the literature on peer influence focuses on negative health behaviors, such as smoking, alcohol and substance-abuse (Dielman et al. 1987; Leatherdale et al. 2006; Fletcher 2012). A few studies have also found peer influence on dietary behavior and physical activity (Birch 1980; Cullen et al 2000; Yakusheva, Kapinos and Weiss 2011), which are important factors in the development of obesity. Although the influence of peers on health behaviors has been of interest to researchers, the influence of peers on obesity has only recently received attention. Peer effects in health behaviors and obesity 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, whereby individuals affect each other by social interactions (for example, Liu, Patacchini and Zenou 2013).

Estimating peer-effects, however, poses several challenges. As laid out in Manski (1993), multiple identification problems arise in a typical peer-effects regression model. These include: a) self-selection into peer groups; b) omitted variable bias that results from the inability to adequately control for environmental features, called correlated factors; and c) the bi-directionality of peer influence and the simultaneous effect of correlated factors on both the individual and the peer outcomes. In a typical social network individuals choose their peers which leads to self-selection bias. In the context of our study, which is on peers in a grade within a school, self-selection could occur by way of parents choosing residential neighborhoods and thereby school attendance zones. Such sorting creates a student body with similar background characteristics attending any particular school. Identification is especially challenging because the correlated factors and the peers' outcome are included as explanatory variables in the same model. This is often referred to as the reflection bias, a special case of simultaneity in estimating peer-effects.

In this study, we exploit a natural experiment that resulted when a number of Arkansas schools were reorganized in response to a state Supreme Court decision on school funding. This created an exogenous reassignment of students from one school to another. We identify the peer-effect by employing an instrumental variables approach on exogenously assigned peer groups to address the self-selection problem. We solve the reflection bias by instrumenting the BMI outcomes of peers with their past outcomes before peer assignment, thus reducing simultaneity bias and the correlation of peer estimate with the correlated factors. This strategy follows Imberman, Kugler and Sacerdote (2012) who used past outcomes as instrument in their study on educational outcomes.

The existing empirical literature studying peer influence on obesity shows mixed findings. Christakis and Fowler (2007) and Yang and Huang (2013), for example, find evidence that friends in a social network influence an individual's likelihood of becoming obese. Cohen-Cole and Fletcher (2008), on the other hand, do not find any peer-effect after controlling for school-specific trends as a proxy for school-level environmental features. Given the challenges in estimating peer-effects, previous studies have understandably focused on addressing a number of the potential biases but not all of them. The above three studies, for example, do not address self-selection into networks. Self-selection into peer groups is important since it might indicate that the groups share similar attitudes, behaviors and characteristics, which could then influence the outcomes.

One of the papers that addressed self-selection is by Yakusheva, Kapinos and Weiss (2014). Using random roommate assignment to address self-selection, the authors find positive peer-effects on dietary and exercise behavior among roommates through the freshman year. They, however, do not eliminate reflection bias. Among studies that address reflection bias, Renna, Grafova and Thakur (2008) and Trogdon, Nonnemaker and Pais (2008) instrument the peers' health outcomes with that of their biological relatives. The argument they use is that genes explains about half the variation in an individual's body weight (Comuzzie and Allison 1998).

No studies to date, however, have been able to convincingly estimate the causal peer-effect on obesity with the exception of Yakusheva, Kapinos and Weiss (2014). Even though the primary place of interaction in their study is assumed to be the dormitory, the campus environment before and after the assignment is similar. This might confound the identification strategy, at least to some extent, because there are many opportunities for social interactions among students who are not roommates. Such interactions could occur in classes and social groups, and the students may also respond differently to the environmental features or programs offered in a university that might influence health outcomes.

In addition to the two significant identification problems discussed above, adequately accounting for environmental features also remains a significant problem. Previous studies use school-specific trends or school-level fixed effects to account for shared environmental features, but these do not account for the actual environment (Cohen-Cole and Fletcher 2008; Trogdon, Nonnemaker, and Pais 2008); and Renna, Grafova and Thakur 2008).

Thus, previous studies on peer-effects on obesity have not fully addressed the identification issues inherent in peer-effects estimation. In this article we identify peer-effects among elementary students by exploiting an exogenous student assignment to schools caused by a court-mandated school reorganization and by employing an instrumental variables method. By design, the methods we use address selection into schools, and partly control for the correlated factors by accounting for the commercial food environment surrounding schools. We also show that the estimation methods we use largely address omitted variable bias and, more importantly, the reflection problem. The implication of the latter is that we can identify peer-effects on obesity in our study.

In contrast to the existing literature that studies adults or adolescence, our research focuses on children in elementary schools. Peer influences have been noted among very young children, ages 2-11 years (Birch 1980). Thus, we focus on elementary school children and investigate if peers are a contributing factor in the increase in childhood obesity rates. Peer-effects, if present, could be leveraged for designing interventions to be more effective by actively engaging peers.

Besides the main contribution of estimating causal links in peer-effects and obesity, our study also contributes in other ways. One, we control for the commercial food environment, including restaurants and grocery stores, around schools and each child's residence with precise geographic data. These constitute correlated factors that could simultaneously influence food consumption among all students in a grade within a school. Two, in contrast to several past studies, the BMI data we use are measured by trained personnel, as opposed to being self-reported. Self-reported height and weight introduces measurement error in the peer measure which biases the peer estimate, and this bias is worse in fixed effects estimation (Johnston and DiNardo 1997). In our analysis, we include various sets of contextual and correlated factors that typically bias peer-effects.

In terms of definition of peers, we follow the same definition generally used in the education literature, which defines peers at a grade-level within a school (Hoxby 2000). Most of the studies on obesity define peers as friends in a friendship network. While a friendship network plays an important role in the behavior of those within the network, a school setting provides a unique environment where students interact daily in a variety of ways that could influence food consumption and physical activity. We focus on peers within the same grade since these students spend a lot of time together and generally have common schedules for school meals, recess times, and physical activities. Peers from specific homeroom classes within a grade could be making closer friendships, but, unfortunately, the data we use does not have such information.

Understanding peer-effects within a school also has some practical advantages for implementing programming aimed at nutrition or physical activity because the peers are already defined (Asirvatham, Nayga, and Thomsen 2014). Identifying friendship networks can take a great deal of effort, and such networks may not be stable over time, particularly among this age group. In contrast, classroom peers are relatively more stable.

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 in the same grade within a school. We also estimate the effect of peers' average BMI z-score. The analytical methods used here largely address self-selection, omitted variable and reflection biases. As mentioned above, to address self-selection into a peer group via parental choices of school or of neighborhood, we use students who were exogenously assigned to different peers, similar to Yakusheva Kapinos and Weiss (2011). We discuss this exogenous peer assignment issue in more detail below. To address the reflection bias, we instrument the peer outcomes by their outcomes before peer assignment, as has been used in previous literature (for example, see Imberman, Kugler and Sacerdote 2012). Since the reassigned set of students were not in the same school before peer group assignment, students from a sending (receiving) school are unlikely to have influenced students from a receiving (sending), thus satisfying the exclusion restriction. The instrument is relevant since a child's current BMI is related to their own past BMI. The test statistics also favor the validity of the instruments used, as discussed in the Results section. The instrument is described in subsection B of the following section on Data and Empirical Strategy.

Our results show a very small standard deviation increase in body mass index (BMI) in response to a one percentage point increase in the proportion of obese students among peers in the same grade within a school. The results in this study are much smaller than the grade-level peer-effect reported by Trogdon, Nonnemaker and Pais (2008).

I. Data and Empirical Strategy

We use the public school elementary student data in Arkansas where childhood obesity rates are among the highest in the country. In 2003, the Arkansas legislature passed the Act 1220 of 2003 that mandated that public school children be assessed for BMI beginning in the 2003-2004 school year. The Arkansas Center for Health Improvement (ACHI) lead the development and implementation of the state-wide BMI assessment process (Justus et al. 2007). ACHI developed a statewide protocol for standardized measurements across the state. Height and weight measurements are measured by trained personnel in schools and reported to ACHI. Student information, including BMI z-scores, race, gender and participation in free or reduced lunches are housed at the Arkansas Center for Health Improvement (ACHI). Only those students with at least two BMI observations are included in our analysis. Based on the CDC reference growth chart, a child is considered obese if his or her BMI z-score falls at or above the 95th percentile on the CDC reference growth chart.

Another source of data we bring into the analysis is location of food businesses obtained from Dun & Bradstreet that include data on restaurants, grocers, and other food stores. Details on the construction of the food environment are provided in Appendix A. Using GIS software, we create measures of the commercial food environment around schools and residences. These variables measure the number and type of restaurants at 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 2004-2010. 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 all grades. Thereafter, BMI was measured and reported only for children in even grades, including the kindergarteners. 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.

A. School Reorganization

We use the exogenous variation created by a school policy to identify peer-effects in childhood obesity. The Public Education Reorganization Act, Act 60 of the Second Extraordinary Session of 2003 was passed as a response to the Arkansas Supreme Court ruling on the *Lake View School District No. 25 v. Huckabee* case. The Lake View School District maintained that the state public school funding was not equitable and fair, in that those school districts in areas with lesser local revenues received less school funding. The State Supreme Court sided with the Lake View School District and ruled that educational funding was inequitable and unconstitutional. One of the ways Act 60 sought to comply with the court decision was through a mandated consolidation or annexation for all districts with fewer than 350 students.

School reorganization thus occurred to overhaul the public school funding system. The primary motivation of this legislation was not to restructure the schools to improve students' health or academic performance. This legislation was instead passed in an extraordinary session of state legislature in response to the court decision. This fact gives credence to our assumption of the exogeneity of peer group assignment that we exploited in this study.

Consolidation is generally bringing schools and/or school districts under fewer management personnel to reduce administrative costs, while annexation involves closing existing schools, opening new ones, or physically merging two or more schools. Thus, in contrast to annexation which affects students, consolidation is more of an administrative change that does not directly require students to change schools. For our research purposes, annexation produces an exogenous variation of changes in schools, and thereby allowing change in peers in a grade within a school. There were 88 schools that were annexed and sent schools elsewhere. These constitute the sending schools in our sample. There were 186 schools that received students from these schools. Since students from both sending and receiving schools were exposed to a new set of peers, students from both sending and receiving schools are included in the analysis.

The legislation affected those in smaller schools, but the students were either moved to a larger school or combined with one or more smaller schools. Whenever a group of students are moved to another school, the students in a receiving school are also affected. Thus we have two sets of students who became peers, who without the reform would not have become peers. This exogenous assignment addresses the issue of self-selection because the school children would not otherwise have been peers.

Table 1 shows that the characteristics of the students in affected schools in our sample are about similar to those of the overall population of public school students in Arkansas. Table 2 shows the differences before annexation across some key characteristics at the school-level between those schools that were annexed (sending schools) and those schools that received them (receiving schools). In terms of obesity prevalence, the two sets of schools are about the same. There is also no difference across gender. But the annexed schools had about 19 percent more African American students and about 14 percent less Caucasian students, with no difference in the proportion of Hispanic student population.

B. Instrumental Variable (IV) Method

Another important bias in the peer-effects literature is the reflection bias that occurs because correlated factors simultaneously influence everyone's BMI and that peers' BMI is the variable of interest. Including measures of the food environment around the schools only partially addresses this because the food and physical activity environment inside schools could be different. So we use past BMI to identify the peer-effects, which has been used in the previous literature on peer-effects (for example, Imberman, Kugler and Sacerdote 2012). By the nature of the reform, we can affirm that a student's current BMI is very unlikely to be correlated with the BMI of exogenous peers before the assignment or relocation because the two groups of students were attending different schools. We test this formally and discuss this in the Results section under Validity Test.

An additional bias could appear because the peer BMI outcomes are also partially determined by peer characteristics, which are predominantly time invariant. Important time invariant characteristics that play a role in determining the BMI outcome could be reflected in gender and race. Meal status, on the other hand, which reflects family income, varies over time. To alleviate concerns of correlation between the contextual characteristics and the endogenous peer effect, we estimate the same model with and without contextual characteristics.

The identifying assumption is that a child's BMI is highly correlated with their past BMI when the exogenous peers were not present in the same school. Given the relatively short period of time from kindergarten through the sixth grade and with the children staying in the same state (Arkansas), we posit that it is unlikely that the BMI outcomes would be random. This suggests that our instrument will be highly correlated with the future BMI. The first stage regression, discussed in the Results section, also shows a strong association.

II. Methods

Our model to estimate the endogenous peer-effect of exogenously assigned peers is based on Manski's (1993) basic peer effects model in a panel framework, and is written as follows:

$$Y_{igkt} = \beta_0 + \beta_1 Y_{-egkt} + \beta_2 X_{igkt} + \beta_3 X_{-egkt} + \beta_4 Z_{kt} + \beta_5 Z_{it} + U_{ikt}, \qquad (1)$$

where Y_{igkt} is the BMI z-score of the i^{th} student in grade *g* of school *k* at time *t*; Y_{-egkt} is the proportion of exogenous peers who are obese 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_{-egkt} 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 the food environment surrounding the school; Z_{it} is the vector of commercial food environment factors around the residence of student *i*; and U_i is the error term which equals $\mu_i + \varepsilon_{it}$, where μ_i is the unobserved time invariant component and ε_{it} is the spherical error term. We primarily examine the effect of exogenous obese peers because these students may have different food preferences or physical activity that may affect choices made by other students. For additional insights, we also re-estimate the model using average BMI z-score instead of the proportion of obese peers.

Following Manski's terminology, β_1 represents the endogenous peer effect. The endogenous peer-effect is measured on an exogenously assigned peer group within a grade in a school. As discussed in the introduction, the grade within an elementary school is the ideal level to represent peer effects because students in the same grade generally share common recess and lunch times, and students within a grade are also assigned to different groups based on their skill in specific subjects.

The peer-effect is identified by employing instrumental variables method on an exogenously assigned group of peers. 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 and also use student-level fixed effects that further reduces the endogeneity bias due to omitted variables in the peer estimate. Since there could be year-to-year changes in a student's 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.

The time- and student-fixed effects (FE) methods, however, do not directly address the bias due to time varying unobservables. These could include dynamically changing physical activity environmental features in some schools that might simultaneously influence student BMI outcomes only in those schools. Note however that we control for school food environment surrounding schools and also around each student's residence which can vary yearly.

Before we discuss the results, it is important to point out that the data used in this study do not contain friendship information to further separate peer influences. However, the estimates reported here are of the exogenous peers and therefore may not simply reflect friendship within classroom. Several students from a given sending school are normally sent to a given receiving school and it is possible that earlier friendships among the endogenous peers will persist after consolidation.

III. Results

In this section, we first present results from the pooled OLS and student fixed effects models and then discuss the results of the fixed effects IV model. Panel A of Table 3 presents the main OLS and fixed effects model results of the effect of exogenous obese peers but without employing the instrumental variable strategy. Since the peer variable is simultaneously determined by all peers in the grade, we also run the regressions with and without the endogenous peers (i.e., those who are from the same school before and after annexation). The peer-effects estimates seem to be affected by the inclusion or exclusion of the endogenous peers. This might indicate that endogenous peers are more influential relative to exogenous peers when it comes to attitudes or behaviors related to food and physical activity choices, and are, therefore, important to include in the model. On the influences of only the exogenous obese peers, the student fixed effects estimate indicates that an increase of one percentage point in exogenous obese peer proportion leads to a 0.00256 standard deviation increase in a student's BMI z-score. The peer-effect is also significant only in the fixed effects model but not in the pooled OLS estimates. This could be because the unobserved time invariant factors influencing BMI outcomes are significant.

To compare the influence of body weight changes of all exogenous peers, in contrast to only the obese peers discussed above, we run equation (1) with the average BMI z-score of the exogenous peers instead of obese peer proportion. Panel B in Table 3 presents the model estimates of the effect of peers' average BMI z-score. The student fixed effects column suggests that the average BMI z-score of a student increases by 0.00272 standard deviations when the peers' BMI z-score increases by one standard deviation. The peers' average BMI z-score estimate is very similar to the peers' obese proportion. This might indicate that the effect of obese proportion dominates or that the effect of not obese is much smaller.

As previously discussed, our identification strategy is to use the IV methods on the exogenously assigned peers. The IV results are presented in Table 4 with the proportion of obese exogenous peers in panel A and the average BMI z-score in panel B. The first stage regression results, which are heteroskedasticity-robust, indicate that the instrument, past obesity status, is a very significant and strong predictor of current BMI. The large F-statistics of excluded instruments could be indicative of high correlation, especially when own past outcome is used as the instrument. The reduced form fixed effects regression also yielded significant estimates of the proportion of past obesity status variable. The coefficient in the pooled OLS when endogenous peers are excluded from the regression produces negative and insignificant estimate (panel A, Table 4). Consequently, the IV estimates using OLS is also insignificant.

The fixed effects IV results show significant effect in the reduced form regression and in the stage 2 regression. After including the endogenous peers, the IV estimates suggest a 0.00341 standard deviation increase when the exogenous peers' obesity proportion increases by one percentage point. This estimate is less than one-tenth decimals higher than the 0.00256 standard deviations observed in the fixed effects model without instrumenting. It might be possible that the unobserved factors downward bias the estimate, which might also explain it's insignificance in the pooled OLS model.

When the average of the past BMI z-score of the exogenous peers is used as the instrument for current BMI z-score, the regression produces a similar result (panel B, Table 4). The first stage is nearly the same as in panel A, but the reduced form regression is significant in the pooled OLS and the fixed effects models. When the past BMI z-score is used as the instrument, the fixed effects IV estimate is about 20 percent smaller than the fixed effects estimate.

C. Instrument Validity Test and Alternative Specifications

An instrument could be invalid if there was a correlation between the body weight outcomes of the exogenous peers before annexation. This could happen if students were interacting outside of schools at the community level. It is important to keep in mind that the schools primarily enroll children within the school attendance zone or their specified geographic area. The attendance area does not overlap across schools offering the same grades. Parents may choose to enroll their child in a school outside of the school attendance zone if: a) the school has an open enrollment policy where they could accept one or more students from within a district or from another area; b) there is extra student space after enrolling all students from the attendance zone; and c) the parent must arrange for the commute to school that is outside of attendance zone. Given the difficulties, it is unlikely that enrollment of students in a school outside of their attendance zone would occur on a large scale. Moreover, open enrollment policy was not commonly adopted in Arkansas during the study period, 2004-2010.

Before discussing the validity test, it is important to point out that the characteristic feature of human body to not fluctuate or respond instantly to environmental features or even health behaviors also makes it difficult to test its validity. Such a test is only possible if the observations on BMI outcomes are apart for a time, during which time the body weight could be influenced by factors that are no longer part of the correlated factors. For this validity test, we use the first two BMI measurements observed right after the annexation. We do not have BMI measurements in all years after year 2007 due to the state policy to measure even grades, and so, are unable to run regression on observations from consecutive years. In Table 5, we show that the first set of observations that we observed right after annexation are significantly associated with the past BMI of the exogenous peers, but it is not significant when the same regression is run using the second set of observations after the annexation. Remarkably, the sign is positive and significant for the endogenous peers in both years. Moreover, the magnitude of the estimate of the endogenous peers is larger in the first year than in the second year they were observed. This validity test thus affirms that: a) BMI outcomes of exogenous peers before annexation did not have any association with the outcomes of the current students; and b) the endogenous peers continue to influence students from the school before annexation. This also implies that the outcomes of only the exogenously assigned peers are valid. While this validity test works when we use past obesity status of exogenous peers as the instrument, it does not show similar results when past average BMI z-score is used.

Apart from this validity test, we also ran student fixed effects regressions under alternative specification. To further address reflection bias, we run student fixed effects regressions with and without the correlated factors, and the results are very consistent (results not included). The one-way and two-way fixed without the shared food environmental features yield identical coefficients up to the third decimal point of magnitude (i.e., 0.294; SE=0.084), which is 0.047 less than the full model peer-effect estimate. Similarly, when we run a regression excluding observable contextual characteristics, the models yield similar peer-effects estimate. For example, excluding the complete set of peer characteristics yields a peer-effects estimate of 0.324 (SE = 0.093) compared to 0.341 (SE = 0.094) when the peer characteristics are included – thus suggesting consistent peer-effects estimates.

IV. Conclusions

This study examined if peers are a contributing factor in the BMI outcomes of elementary students in public schools. Studying peer-effects on obesity is important because peer influences could be harnessed to foster positive dietary behaviors or physical activity choices. The existing literature has not adequately addressed most of the typical biases in estimating peer-effects, and also shows mixed findings ranging from no effect to some significant effects. The mixed findings could be due to different sets of information being used across the studies. In our regression models, we include a rich set of variables that control for individual and peer characteristics and also the food environment surrounding schools. We argue that the exogenous peer assignment that we exploited due to school reorganizations removes most of the self-selection bias. Using information from before the peer assignment as instruments, we reduce the impact of reflection bias and correlation with other unobservables on the endogenous peer-effects estimate. Since the instrument is the outcome of one's own past outcome, we use student fixed effects to eliminate further bias arising from the correlation of time constant unobservables. Furthermore, unlike most studies examining peer-effects and obesity, students' BMI used in this study is measured by trained professionals, which eliminates attenuation bias prominent in the fixed effects model. Another important factor ignored in this stream of existing literature is 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. All our models include year fixed effects. Our analysis suggests that an increase of one percentage point in the proportion of obese students in a class would lead to a very small increase 0.00341 standard deviations in the BMI z-score of a student.

There are some limitations of this study. One, 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 that they vary with time, could affect student choices and the fixed effects methods only partly address this issue. Hence, some biases due to the presence of time varying unobserved factors might still remain. Two, we do not have any information on specific policies related to nutrition and physical activity. Lack of such information might underestimate the endogenous peer-effects estimate.

While our study does indicate consistent peer-effects within a grade among elementary public school students, the effect is very small at the grade-level. This is in line with the argument posed by Trogdon, Nonnemaker and Pais (2008) that classroom peer-effects could be smaller because of inclusion of students outside of relevant social network of influence or friendship.

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VI. Tables

TABLE 1: SUMMARY STATISTICS FOR THE STUDENT SAMPLE

Variable	Population*	Regression Sample
BMI category		
Underweight	0.018	0.017
Normal weight	0.601	0.582
Overweight	0.174	0.175
Obese	0.207	0.226
Race		
Caucasian	0.647	0.602
African American	0.228	0.344
Hispanic	0.074	0.031
Native American	0.004	0.003
Asian	0.013	0.006
Other or Unknown	0.034	0.014
School meal		
Free meals	0.476	0.475
Reduced meals	0.099	0.090
Fully paid	0.425	0.435
Nearest food store		
Nearest grocery (miles)	3.02	4.13
Nearest dollar (miles)	2.86	3.32
Near convenient store (miles)	1.58	1.84
Nearest fast-food (miles)	2.55	2.93
Nearest pizzeria (miles)	4.15	5.42
Nearest sandwich (miles)	2.76	3.27

Table 1 contd.

Table 1 contd.

Variable	Population*	Regression Sample
Other demographics		
Female Proportion	0.487	0.491
Age (months)	104.83	129.67
Rural	0.285	0.318
Urban	0.582	0.536

*This population includes all students in grades K-6 and who have at least two annual observation.

TABLE 2: KEY CHARACTERISTICS (PERCENT) BEFORE ANNEXATION BETWEEN SCHOOLS THAT MERGED AT THE GRADE-LEVEL.

Peers' proportion	Sending Schools (N=88)	Receiving Schools (N=186)	Difference‡
Obese	15.26	14.89	0.0.37
	(11.07)	(10.42)	(6.06)
Caucasian	41.37	55.61	14.23***
	(41.01)	(28.04)	(29.77)
African American	60.24	41.46	18.78***
	(43.61)	(32.24)	(26.83)
Hispanic	4.68	6.95	2.27
	(6.68)	(13.04)	(14.59)
Boys	54.77	54.59	0.18
	(7.49)	(3.81)	(7.56)
Girls	52.07	50.76	1.31
	(6.70)	(3.40)	(6.73)

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

‡ Paired T-test was conducted to test for the statistical difference.

TABLE 3: ESTIMATE OF EXOGENOUS OBESE PEERS ON STUDENT'S BMI Z-SCORE

Peers' variable	Excluding endogenous peers		Including endogenous peers	
	OLS	Student FE	OLS	Student FE
Panel A				
Obese proportion	-0.131	0.345***	0.165	0.256***
	(0.116)	(0.098)	(0.122)	(0.089)
Panel B				
Average z-score	-0.039	0.168***	0.169***	0.272***
	(0.040)	(0.059)	(0.045)	(0.063)

Note: Regressors in each regression model include student age, race, gender, rural/urban area of residence, participation in school free/reduced lunch program, year dummy variables, and the commercial food environment around student residence and school. The student fixed effects (FE) model includes student fixed effects in addition to the other regressors listed. School-level clustered standard errors are in parentheses. N=37,556

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Robust clustered standard errors are given in parenthesis.

TABLE 4: INSTRUMENTAL VARIABLES ESTIMATE OF EXOGENOUS PEERS' BMI OUTCOMES ON STUDENT'S BMI Z-SCORE

Peers' variable	Excludes endogenous peers		Includes endogenous peers	
	OLS	Student FE	OLS	Student FE
Panel A: Obese proportion				
Obese proportion	-0.201*	0.298***	0.150	0.341***
	(0.107)	(0.087)	(0.119)	(0.094)
Reduced Form				
Obese proportion pre- annexation	-0.203*	0.304***	0.148	0.334***
	(0.109)	(0.088)	(0.118)	(0.093)
First Stage‡				
Obese proportion pre-annexation	1.015***	1.019***	0.987***	0.993***
	(0.013)	(0.016)	(0.014)	(0.017)
F-stat of excluded instrument	5,992	4,155	4,540	3,485
Panel B: Mean z-score				
Mean z-score	-0.072**	0.097***	0.132***	0.220***
	(0.034)	(0.030)	(0.042)	(0.035)
Reduced Form				
Mean z-score pre-annexation	-0.069**	0.094***	0.120***	0.210***
	(0.034)	(0.029)	(0.038)	(0.033)
First Stage ‡				
Mean z-score pre- annexation	0.958***	0.966***	0.953***	0.944***
	(0.006)	(0.012)	(0.013)	(0.013)
F-stat of excluded instrument	26,157	6,885	17,895	5,713

Note: Regressors in each regression model include student age, race, gender, rural/urban area of residence, participation in school free/reduced lunch program, year dummy variables, and the commercial food environment around student residence and school. The student fixed effects (FE) model includes student fixed effects in addition to the other regressors listed. School-level clustered standard errors are in parentheses. N=37,556

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Robust clustered standard errors are given in parenthesis.

‡ Dependent variable in the first stage is the proportion of exogenous peers in the respective weight category in the current period. Each estimate of the first stage regression is from a separate regression.

TABLE 5: ESTIMATES OF THE PROPORTION OF THE EXOGENOUS AND ENDOGENOUS OBESE PEERS ON STUDENT'S BMI Z-SCORE ONE AND TWO YEARS AFTER ANNEXATION ON STUDENT'S BMI Z-SCORE

Peers' proportion	One Year (N=15,916)		Two Years (N=15,904)	
	Exogenous	Endogenous	Exogenous	Endogenous
OLS	-0.451***	0.389***	-0.206	0.257***
	(0.175)	(0.097)	(0.167)	(0.091)
OLS with grade FE	-0.492***	0.314***	-0.215	0.182**
	(0.175)	(0.098)	(0.167)	(0.092)

Note: Regressors in each regression model include student age, race, gender, rural/urban area of residence, participation in school free/reduced lunch program, year dummy variables, and the commercial food environment around student residence.

*** Significant at the 1 percent level.

** Significant at the 5 percent level.

* Significant at the 10 percent level.

Robust clustered standard errors are given in parenthesis.

APPENDIX

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 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 establishments 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.