PEER-EFFECTS IN OBESITY AMONG PUBLIC SCHOOL CHILDREN:

A GRADE-LEVEL ANALYSIS

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ABSTRACT

We examine the role of peer effects in childhood obesity outcomes by investigating whether obesity rates among the highest graders in a public school has an effect on obesity rates among younger grades. We use a panel dataset with obesity prevalence measured at the grade level. Our data are from Arkansas public schools. Results provide evidence that changes in the obesity prevalence at the highest grade are associated with changes in obesity prevalence at younger grades. The magnitude of the peer effect depends on the type of school, and we find statistically significant peer effects in both elementary and high schools but not in middle schools. These effects are also larger in high schools than in elementary schools. We use falsification tests to provide evidence that these peer effects are more than just a statistical correlation or an association.

INTRODUCTION

Obesity is a growing epidemic in the United States (US). Among children and adolescents, ages 6 through 19 years, the obesity incidence has increased from about 4.2% in 1960s to about 17 % in 2007-08 (Surgeon General's report, 2001; Ogden et al., 2002; Ogden et al., 2010). The increasing prevalence of childhood obesity is an important issue because of the negative health implications from childhood through adulthood related to both morbidity and mortality (Serdula et al., 1993[a]; Kindblom et al., 2009[1]). The long term effects of childhood obesity on health have also been found to be worse than that of adult obesity (Olshansky et al., 2005). Consequently, an increasing number of studies have focused on childhood obesity.

The main focus in the literature has been on understanding the mechanisms through which more calories are ingested or whereby less calories are expended (Bleich et al., 2011). More recently, studies have focused on peer influence on obesity. This is especially important because peer groups can support and/or reinforce the determination to attain or maintain healthy weight (Christakis and Fowler, 2007; Halliday and Kwak, 2009). A peer group can also complement various interventions aimed at improving health behaviors and health. For example, Christakis and Fowler (2007) posit that programs, such as smoking and alcohol cessation, which provide peer support are more successful. This lends support for programs which exploit peer effects to achieve better health and/or to promote healthful choices. Our results, using panel data methods, support such findings even in the context of schools where reference peers are defined as the highest grade in a school, as opposed to students within each grade.

Christakis and Fowler (2007) were the first to report a more rigorous study of peer effects on individual obesity. Their findings, as described in Fowler and Christakis (2008), clearly show

[1] The sample in Kindblom et al. included only men.

that peers do influence obesity. A few other studies report similar findings, thereby confirming the existence of peer effects on obesity (Cohen-cole and Fletcher, 2008; Renna et al., 2008; Trogdon et al., 2008; Yang and Huang 2011). Evidence in the literature also strongly supports the notion that positive peer influences can have an impact on positive behavior, particularly in reducing, dissuading, or discouraging smoking, substance abuse, sexual activities, and other risky behaviors (Botvin et al., 1984; Clarke et al., 1986; Leatherdale et al., 2006). For instance, schools have used high school students to reduce the peer pressure among elementary school students towards substance abuse (Stock et al., 2007). There is also evidence in the literature that older peers are effective in influencing positive change. Cohen et al. (1989), for example, found that teacher and older peer-led interventions showed significantly more improvements on nutrition of both the older and younger peers when compared to interventions led only by teachers.

Even though studies find significant influences of peers in a social network, the school setting presents a unique environment where peers in different grades could influence each other's behavior. For example, younger students may look to older graders as role models when it comes to attitudes about body image, the importance of academic or sports achievement, and other desirable or undesirable attributes or activities. Peer effects have been shown to be especially important in affecting deviant behaviors among younger graders in a school (Alexander et al., 2001; Leatherdale and Manske, 2005). More to the point of our study, in select Canadian schools, Leatherdale and Papadakis (2011) found a higher likelihood of a 9th or 10th grader being overweight/obese if that student attended a school with a high prevalence of overweight senior students (11th and 12th grade). This study contributes to this body of literature by examining the influence of peers on the prevalence of obesity across grades in schools. More specifically, our objective is to analyze whether the obesity rate among older peers influences that of younger graders. In our study, we use a panel dataset based on Arkansas public schoolchildren. Our data have an advantage in that grade-level obesity rates are based on measured, not self-reported, heights and weights of students. These measurements were taken by trained personnel within the public school system. Thus we are able to obtain more reliable and consistent estimates of peer influence of obesity across grades in public schools. That said, these data are subject to strict confidentiality and so only grade-level aggregates could be released for use in our study. Our use of grade-level aggregates represents another difference between this study and others that have examined peer effects among youth.

Targeting interventions to oldest peers in a school has some advantages. Hoxby (2000) argued that peer-effects can be considered an externality that can have positive multiplier effects within schools, and it would be more efficient to internalize such effects while developing appropriate policies. Moreover, older graders tend to become more conscious of the choices they make when they are made aware of their leadership role (Cohen et al., 1989; Stock et al., 2007). Finally, it might also be much easier to educate older graders because of their relatively higher cognitive development.

We also examine whether the effect of older peers on younger peers varies by type of school (i.e., elementary, middle school, high school). Children perceive their family and peers differently depending on their stage of development (Lynch and Cicchetti, 1997). Consequently, peer effects can be expected to vary by school type. Since younger school children can be exposed to older peers of different ages, depending on the grades offered in a school or school type, we not only examine if there are differences in peer influence across school types (elementary, middle, high school) but also across school subtypes. For example, elementary schools in our sample differ with some housing kindergarten (K) through 4th grade, others K through 5th grade, and others K through 6th grade.

HOW MIGHT OLDER PEERS INFLUENCE YOUNGER PEERS' BMI?

Peers are defined variously in the literature. Studies on gender composition define peers by the proportion of females in a classroom (Hoxby, 2000; Lavy and Schlosser, 2011). Christakis and Fowler (2007) defined peers as friends in their network, and specifically those whom they consider as friends. Studies on peer-effects in a school-setting sometimes consider peers as fellow classmates or pupils in the same grade (e.g., Hoxby, 2000). Although peers in the same class or grade influence each other, older peers can also be an important influence (Morgan and Grube, 1991). In our study, we define peers as the highest graders in a school and examine the effect of obesity among these older peers on obesity rates of children in lower grades. Previous studies on influences across grades within schools have generally focused on health behaviors such as smoking, substance-abuse, and alcohol use (Harris and Lopez-Valcarcel, 2008; Kremer and Levy, 2008). To our knowledge, no other study has examined the role of older reference peers on obesity outcomes among children and adolescents.

While our data are not adequate to decipher the reasons behind the peer effects, it is important to discuss the mechanisms through which the obesity rate of older graders' affects younger graders. The main argument is that younger children look to the older peers as role models. Some studies have found that the effect of peers are stronger with unhealthy behavior, including smoking, alcohol, substance abuse, etc. (Dielman et al., 1987). For example, Leatherdale et al. (2006) examined Ontario (Canada) schoolchildren and found that the odds that a 6th or 7th grader smokes increases with the percentage of smokers among 8th graders. They also found that the effect of older peers was more pronounced for those students who had no family member or friend who smoked.

To the extent that younger children model the behaviors of older peers, older children could impact the obesity outcomes through both calorie intake and calorie expenditure. Calorie intakes can be affected if older graders send signals, through actions or comments, that healthful foods are not "cool foods" or possess lesser gastronomic properties. Food marketing research shows that food manufacturers associate their products with good times, appealing taste, or contexts considered to be hip or cool for increased marketability of their products (Folta et al., 2006; Harris et al., 2009), and it is possible that older children could reinforce these messages through their attitudes or behaviors. Older peers might also influence calorie expenditure if younger children take cues from the involvement or lack of involvement of older peers in physical activities. Previous research has shown that obese children are physically less active and also less likely to participate in team sports (Storey et al., 2003; Forshee et al., 2004).

In addition to food choices and physical activities, body image can also play an important role, particularly in the middle and high school (Serdula et al., 1993[b]). Perceptions of body image could affect the dietary behavior and physical activity, especially with the onset of puberty (Fisher et al., 1994; Heinberg et al., 2001; Littleton and Ollendick, 2003). Attempts to maintain or achieve a slimmer body that is considered more attractive or pleasing can make children more conscious of their choices[2]. It is also possible that the ideal weight of younger graders or their tolerance for obesity increases with increased weight of older graders (Burke and Heiland, 2007).

[2] However, we do note that the children might make unhealthful choices and adopt unhealthful behavior (e.g., dieting, bulimia-nervosa, anorexia, etc) to achieve better body image (Levine et al., 1994; Littleton and Ollendick, 2001).

The influence of older peers could also change based on the growth and development of children. For instance, Lynch and Cicchetti (1997) found that middle school children are more likely to be influenced by peers than elementary school children. Furthermore, in our data younger school children can be exposed to older peers of different ages, depending on the grades offered in a school or school type. For example, 2nd grade children in K-6 elementary schools will confront older children than 2nd grade children in K-4 elementary schools. Some studies found differences across grades in academic outcomes, rates of infraction, and satisfaction with own body image depending on the grade levels included within the school (Blyth et al., 1985[3]; Bedard and Do, 2005; Cook et al., 2008). Therefore, it would be useful to not only know if older peers influence younger school children, but also if such peer effects vary by school types or subtypes. Hence, in this study, we not only examine if there are differences in peer influence across school types (elementary, middle, or high school) but also across school subtypes based on the grade-levels housed within the school.

DATA

We focus our analysis on schools in Arkansas. Arkansas is an interesting case to study since it is one of the poorest states and is also one of the least educated and least healthy. More importantly for our study, the Arkansas's childhood obesity rate has doubled in the last couple of decades and is one of the highest in the country (Arkansas Center for Health Improvement (ACHI) 2009).

[3] Blyth et al. examine differences in satisfaction with body image among 6th graders in K-6 schools to those in K-8 schools. The latter school type has a much older set of peers.

Table 1 provides descriptive statistics for the dataset used in this study. Grade level obesity rates were obtained from ACHI and represent the primary variable of interest. The obesity rate is based on the body mass index (BMI) for age and gender specific percentile based on the National Center for Health Statistics (NCHS) growth charts for children and adolescents developed in 1977[4]. According to the standard definition, a child or adolescent is considered obese if he or she falls at or above the 95th percentile on the growth chart, and is considered overweight if at or above the 85th but below the 95th percentile. Beginning in 2004, Arkansas law has required that the height and weight of each child be measured by trained personnel within the public schools. The fact that our data are based on actual weight and height measurements is one important advantage of the obesity rates used here. However, these BMI screenings are subject to strict confidentiality protections and so only grade level aggregates are in the public domain. Other variables used in the study (see table 1) measure characteristics of the school, school-district, or county and are included as controls in the regression models.

Our empirics are based on a panel dataset covering the years 2004 to 2009. 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 2006, obesity prevalence rates are available annually for grades K - 12. Thereafter, obesity rates are measured and reported only for even grades through the 10th grade (K, 2, 4, 6, 8 & 10). Thus we have BMI prevalence rates for all grades from 2004 through 2006, and for even grades from 2007 through 2009, which makes the data an unbalanced panel by school and grade. Since the decision to stop measuring the BMI of children in odd-numbered grades was not made by the child, the child's family, or the school, the non-reporting of obesity prevalence in these grades should not bias our estimates.

[4] The Centers for Disease Control and Prevention (CDC) has updated growth charts in 2000. http://www.cdc.gov/obesity/childhood/basics.html

However, this change in reporting does affect our ability to define the obesity prevalence of highest grade peers in a consistent fashion over time. In our analysis, we only include those cohorts for which highest-grade peers were measured. For example, cohorts in K-5 elementary schools are included in our study only for 2004 through 2006 because these are the only years in which 5th grade prevalence rates were measured. On the other hand, cohorts in K-6 elementary schools appear in our study throughout the entire sample period.

The cross sectional unit used in our analysis is the cohort and so it is important to explain what this term means within the context of our dataset. We define cohorts by class within a school. The number of times a cohort is observed depends on the type of school and the time period in which the class is first observed. To illustrate, the 2004 kindergarten class at a given K-6 elementary school would form a cohort in this study. We first see this cohort in 2004 as kindergartners and then again in 2005 and 2006 as 1st and 2nd graders, respectively. Because BMI measurements switched to even-only grades in 2007, we do not observe this cohort again until 2008, at which time members of this cohort are 4th graders. Similarly for this school we would define other cohorts by class and their first appearance in our dataset. Since 2004 is the first year represented in our data, the 2nd, 3rd and 4th grade classes at this K-6 elementary school would also represent cohorts. In later years (2005-2009), the entering kindergarten classes would represent additional cohorts. Our regression models include all available time series observations on cohorts until they reach the penultimate grade housed within the school. When the cohort represents the highest grade in the school, they are no longer included as an observation in our models. Instead, this cohort becomes the highest-grade peer group and their obesity prevalence is used to measure the reference-peer obesity rate for all younger cohorts within the school. Cohorts in each school are consistently defined in similar fashion.

While prevalence rates are commonly used in research and in policy discussions, one caveat to using them as an outcome measure is that obesity prevalence only captures the fraction of students transitioning across a cut-off point, in our case the 95th percentile-definition of obesity. Consequently our analysis would not capture BMI changes within those already classified as obese. Nor would it capture BMI increases within other weight categories that are insufficiently large to cause reclassification of individuals from normal or overweight to obese. In other words, constant prevalence rates do not mean that BMI has not changed.

There are several other data issues that deserve mention. One is that confidentiality protocols prevent grade-level obesity rates from being reported when only a small number of students are over the 95th percentile BMI category. However, our data do contain the number of children that were measured for BMI by school and grade and we have access to school level obesity rates reflecting all grades. In investigating this issue, it was clear that such non-reporting is primarily from small-enrollment schools and not from schools where obesity is less of a problem. Secondly, the structure of some schools changed over the study period in that they dropped grade levels or added additional grade levels. This was due, in part, to restructuring of school districts that occurred in 2004 through 2005 and that resulted in the consolidation of some schools and school districts. Because the age of highest-grade peers might influence younger graders differently, we excluded all cohorts from those schools which changed the highest grade during the study period. Exclusion of these schools reduced the sample size, but was essential to build a more consistent panel dataset of cohorts and to ensure reliable estimates. Lastly, across Arkansas there is substantial variation in methods of housing the various grades, especially the intermediate grades, grades 6 through 9. Given the heterogeneous school structure, we restrict our analysis to the most frequent types of schools and group these broadly into elementary, middle and high schools as follows:

- *Elementary Schools*: Schools housing grades K-4, K-5, or K-6.
- *Middle Schools*: Schools housing grades 5-8, or 6-8.
- *High Schools*: Schools housing grades 9-12 or 10-12.

We estimate models for (1) an overall sample including all schools; (2) subsamples for elementary, high school, and middle schools; and (3) subsamples for sub-types such as K-4 elementary schools, 9-12 high schools, etc.

MODEL

Our model is based on Manski's (1993) basic peer effects model in a panel framework, the peer effects of the j^{th} (or highest) grade on the i^{th} younger grade in school k at year t can be written as:

$$Y_{ikt} = \beta_0 + \beta_1 Y_{jkt} + \beta_2 X_{ikt} + \beta_3 X_{jkt} + \beta_4 Z_{kt} + U_{ikt}$$

where, Y_i is the obesity prevalence of the respective cohort, Y_j is the obesity prevalence at the highest grade, X is the grade characteristics, Z is the vector of other school level characteristics, and U_i is the spherical error term. The cohort, in the above equation, is defined by the i^{th} grade in school k. Later in the analysis we address the assumption of the unobserved time invariant components. β_2 is the column vector of the coefficients of i^{th} grade level characteristics, β_3 is the column vector of the coefficients of j^{th} grade level characteristics, β_4 is the column vector of the coefficients of k^{th} school level characteristics, and β_1 is the coefficient of interest in this study which is the effect of the j^{th} highest graders' obesity rate on the younger graders in the same k^{th} school.

Following Manski's terminology, β_3 represents contextual effects; β_4 represents correlated effects; and β_1 represents the endogenous peer effects. Correlated effects arise because of similar characteristics of the graders or the similar environment where they interact or study. Here school is the common place where both graders interact and hence school characteristics would represent the correlated effects. Contextual effects are represented by the demographics and related characteristics of the peer group.

The dataset we used in this study does not have grade specific information other than weight variables, which does not allow us to control for either X_i or X_j. Some of the school characteristics in Z vary over time (Z_{1kt}) while some do not (Z_{2kt}). Not controlling for grade-level characteristics over time could bias the estimates by way of omitted variable bias. The dataset we used in this study, however, has a good amount of information at the school and school district levels. Therefore, all information specific to the grade-level that differs from that at the school-level would be included in the error term. There are unobserved factors that might increase obesity prevalence among younger grades such as the availability of vending machines, fast food restaurants around schools, and other unhealthful environmental features. These might also increase obesity prevalence even among the highest grades. There could also be factors that might counter the increase in obesity prevalence such as programs that increase physical activity levels and those that create an environment for more healthful choices. Since factors promoting obesity are more prevalent, we expect a positive bias in the OLS estimates. If most of the omitted variables are time invariant, then OLS is generally biased upwards but the within estimator or any model that controls for time invariant unobservables is consistent. Using different estimation methods we show that our results are quite robust despite these limitations.

In addition to the school environment, parental school choice could affect child health outcomes, as has been noted in the academic performance literature (Bauch and Goldring, 1995). Parents with more interest in academics or sports might choose schools that perform better in their field of interest. Similarly, parents who are more conscious of health and nutrition might choose schools that have healthful environment. The evidence of school choice based on healthful environment, however, is lacking (Hoxby, 1999). 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.

We mostly rely on fixed effects and the within estimator to obtain consistent estimates. Several other regressions are also presented that show a more or less consistent story on the peer-effects across grades. The OLS regression that includes cohort fixed effects (time invariant) is referred to as the Least Squares Dummy Variable (LSDV) model. The LSDV estimator accounts for bias in the peer-effect estimate due to its correlation with the time invariant unobserved component. Since there could also be yearly trend in the prevalence rates at the younger grades that might bias the estimates, we also estimate a time-varying but cohort fixed effects, i.e., two-way fixed effects[5].

Other than modeling issues, some concerns have been raised on the definition of peers. Even though using grade-level cohort in a school is more standard in the peer literature, Halliday and Kwak (2012) raised some pertinent estimation problems with this definition. According to

[5] This is achieved by including year dummies in an LSDV model.

them, such definition can lead to omitted variable bias by not controlling for the heterogeneity across schools; collinearity between the peer network's behavior and school fixed effects; and weak instruments due to simultaneity bias. We address these issues using a variety of specifications and tools in the results sections. It is important, however, to note that the use of grade-level cohorts could yield results that can be used to design programs that could be implemented more generally, even in schools where identifying peers itself might be a significant hurdle and costly. It is also more practical to assess changes in behaviors at the grade level.

RESULTS & DISCUSSION

Table 3 presents results using a sample of all schools pooled together. The OLS estimate shows a 0.13 percent increase in obesity prevalence among younger graders for every one percent increase in the obesity prevalence among highest graders[6]. However, the magnitude of the estimate decreases to 0.05 after including cohort fixed effects. As expected, this suggests that some unobserved components that influence obesity prevalence among younger grades could be correlated with obesity prevalence among highest graders, leading to upward bias in models that do not control for such fixed effects (Lewis, 1986). Based on the rejection of the Hausman test[7], which tests for the equality of the random effects and within effects estimates, we conclude that time invariant unobserved factors at the grade level are correlated with the estimates.

[6] This estimate is slightly lower, 0.36, when the 12th graders are included as the highest grade.
[7] Hausman Test: chi-square value = 144 (p-value: 0.00001) for the test between random effects (0.09; SE: 0.012) and within estimates (0.05; p-value: 0.015) of the highest grade.

To assess possible differences in peer effects across school types, we estimate the model for subsamples representing elementary, middle, and high schools. Results are presented in table 4. The effect of the highest grade from OLS models is 0.16 for the elementary schools, 0.07 for middle schools, and 0.18 for high schools. After controlling for cohort fixed effects, the coefficient decreases to roughly one-third of the OLS magnitude in all the school types; i.e. to 0.05 for elementary schools; 0.03 for middle schools; and 0.07 for high schools. The estimates for middle school, however, are insignificant as are the LSDV and within estimators for high schools. Another important result to note is that the coefficients for elementary schools are nearly identical in both the one-way and two-way LSDV methods, but not so for high schools. In high schools, the standard error is higher when year dummies are included. The level of significance changes from $p = 0.12$ to $p = 0.20$, even though the coefficient is nearly the same.

As discussed above, there could be differences across school subtypes. Specifically, we test if the coefficients are the same across schools with different grade offerings. In other words, we wish to know if younger grades are affected differently based on the ages of the older peers. In Table 5, both the LSDV and within estimates are 0.10 for the K-4 school subtype, near 0 for the K-5 subtype, and 0.05 for the K-6 subtype. Among middle schools, the estimates remained insignificant even for school subtypes, 5-8 and 6-8. Interestingly, peer influence in high schools varied by subtypes as in the case of elementary schools. Schools with 9^{th} -12^{th} grades showed no influence but those with 10^{th} -12^{th} grades showed very high influence of the prevalence of obesity at the 12^{th} grade on the 10^{th} and 11^{th} grades.

Another important result that we find is the differential bias of unobserved components in elementary and high schools. Some unobserved factors, such as the availability of vending machines, could cause an upward (or positive) bias of the coefficient on the highest grade, while some factors, such as programs to reduce obesity prevalence, could cause a downward (or negative) bias. The unobserved factors that could cause upward bias appear to dominate in elementary schools and elementary-school subtypes, while those factors that could cause downward bias appear to dominate in high schools and especially within the 10-12 school subtype.

FALSIFICATION TESTS

In this section we show, in two ways, the statistical insignificance of the 'evidence against' highest grade effect. First, we show that while the highest grade affects younger grades when housed within the same school, these affects cease after the highest grade leaves. Lavy et al. (2011) conducted a similar test in assessing peer-effects in academic performance, in which they used units in levels[8]. In this study, we used differences or changes because of the persistence of obesity (Dietz, 1994). Current highest graders were present in the previous year, so their influence would most likely be present in the prevalence measures of younger graders in the previous year. Thus past changes in the obesity prevalence among younger graders are influenced by current highest graders. But the current highest graders are not present in the following year, so the difference between current and future obesity prevalence among younger graders should be 'independent' of the current highest grade.

As conjectured, the regression results in Table 8 show significant influence only among graders who are currently in the school. The results of regressing future difference on current highest graders show no significant influence, but yielded significant estimates in past difference

[8] They used balancing test to show that their instrument, repeaters proportion does not affect lag or future peer academic outcomes.

when the existing highest graders were present[9]. The fact that we do not find statistical significance in the lower panel provides evidence that highest graders have no influence on the obesity prevalence among younger graders once the highest graders have left the school. This finding provides evidence that the observed peer effects are indeed the outcome of interactions with reference peers and are not just a statistical artifact.

Secondly, we test if the prevalence of highest graders classified as overweight but not obese (those between the 85^{th} and 95^{th} percentiles) drives the prevalence of those classified as obese among younger graders. In doing so, we also test if there are cross-effects across different weight categories. This is particularly relevant in an obesity study because obese children are visibly different from children that are overweight but not obese. Thus the behavior of obese children could also be more noticeable, whether markedly different or not, than children in other weight categories. In the analyses, we re-estimated the obesity prevalence regressions after including overweight prevalence at the highest grade as an additional regressor. The first observation to note is that the prevalence of overweight at the highest grade does not influence prevalence of obesity at lower grades (Table 9A, 9B, and 9C). This result is consistent across different school types and subtypes. The second noteworthy observation is the consistency of the estimates on highest-grade obesity prevalence with those reported earlier in Tables 3 through 7[10].

Based on these falsification tests we conclude that the effect of the obesity prevalence at highest grade on obesity prevalence at younger grades is more than just a correlation. An

[9] Future difference in obesity outcome = $Y_{t+1} - Y_t$; and past difference = $Y_t - Y_{t-1}$.

[10] Likewise the overweight prevalence among younger grades was regressed on overweight prevalence and obesity prevalence at the highest grade. The consistency is also observed for the estimate of overweight prevalence in the overweight model. This leads us to conclude that the two weight groups do not influence each other significantly, and that they do not exhibit collinearity.

additional test strategy would be to instrument obesity provenance amongst the highest grade with the prevalence of the prior year's highest grade. This instrumental variables approach proved to be infeasible because of the significant reduction in sample size and accompanying reduction in statistical power.

SUMMARY AND CONCLUSION

This paper provides evidence that changes in the obesity prevalence at the highest grade is associated with changes in obesity prevalence at younger grades. Overall, our results indicate that a one percent increase in the prevalence of obesity among students in the highest grade increases the prevalence among younger graders by 0.05 percent. In other words, for every 20 highest graders becoming obese, one younger grader becomes obese. Using falsification tests, we provide evidence that this finding is more than just a statistical correlation or association.

When assessing differences across school types, we find that peer effects are lower in elementary schools, slightly higher in high schools, and negligible in middle schools. In particular, one younger grader becomes obese for every 20 that are obese in the highest grade among elementary schools and for every 14 that are obese in highest grade among high schools. This indicates a greater influence of higher grade peers during adolescence. Possible explanations include a growing awareness of self-image, pubertal growth, or perceptions of peers in high schools. This finding is not unexpected as social interactions are more common among adolescents in high school (Yang and Huang, 2011). However, it is not clear why we do not see peer effects in middle schools. Perhaps pubertal growth spurts, which occur between 11 and 14 years, could induce more randomness in the measured BMI percentiles within a cohort and/or among highest grades (Hamill et al., 1970). Such random variation would be more pronounced in middle schools when growth spurts generally occur. This might preclude any systematic association between the younger peers and highest grade. It is also possible that we are not getting as much statistical power in our middle school estimates due to smaller number of middle schools in our sample.

The estimated peer effects are more pronounced when children are closer in age to their highest-grade peers. Specifically, within elementary schools, results show that the highest-grade peer effect is larger in K-4 schools than in K-6 schools. Interestingly, one younger grade child becomes obese for every 10 4th grade children that are obese in K-4 schools. Similarly, among high schools, we find that peer effects in 10-12 schools are statistically significant while those in 9-12 schools are not. In 10-12 schools, one younger grade adolescent becomes obese for every six 12th graders that are obese. These findings suggest that the peer effects we are finding do reflect social ties and are more than just a simple reflection of geographic proximity. Our findings are consistent with Yang and Huang (2011) in this respect. If geographic proximity was the main cause of the observed peer effects, then one would expect the peer effects in K-4 schools to be similar to those in K-6 schools and also that peer effects in 9-12 schools would be similar to those in 10-12 schools.

Such peer effects were not observed in K-5 schools, after controlling for individual grade-level or cohort fixed effects. It is important to note that K-5 schools are not directly comparable to K-4 and K-6 schools because unlike these, K-5 schools report prevalence at highest grade only during the shorter 2004-2006 sample period.

Peer effects are rarely taken into account by policy makers. Yet our findings suggest that peer effects could generate multiplier effects (Glaeser et al., 2003). Policy interventions targeting older peers in public schools, particularly in elementary and high schools, may be effective in reducing childhood obesity rates. Interventions that consider the grade-level may be more efficient than individual level interventions alone. Given the current climate of limited funding, it is prudent for policy makers to use peer-effects to their advantage.

The role of peer effects on obesity does require further study. Specifically, studies using individual level data, as opposed to grade level data, may provide more definitive estimates of peer effects in schools. It would also be useful to incorporate behaviors of teachers or family into analyses of peer effects. One earlier study, for example, found a positive association between smoking by teachers and smoking among students (Piontek et al., 2008), and it is possible that students may also take cues related to diet or physical activity from the behavior of adults in their environment. Given data availability, future studies should also examine the mechanisms through which older peers affect younger graders' obesity rates. Possible mechanisms that could be evaluated include those related to eating patterns, physical activity or inactivity, weight management activities, and imitative obesity (Blanchflower et al., 2009). Such knowledge on the underlying causes of peer effects will allow public health interventions to emphasize areas with largest potential to reduce childhood obesity.

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Table 1: Summary statistics of variables included in the regression by school types.

Variable	Elementary (N=4,919)		Middle (N=359)		High (N=794)	
	Mean	SD	Mean	SD	Mean	SD
Race, gender, rural (%)[A]						
White	69.22	28.81	74.92	28.17	69.96	28.05
Black	20.99	27.46	20.65	28.13	24.74	28.91
Asian	1.40	2.60	0.79	1.38	1.16	1.76
Hispanic	7.80	12.59	3.06	3.48	3.53	5.54
Native	0.59	0.88	0.58	1.05	0.61	1.16
Female	48.66	2.65	48.79	2.70	49.18	2.66
Rural	2.02	2.41	69.78	31.66	54.73	31.29
Rural farm	1.90	2.30	2.83	2.28	2.31	2.32
Income ($)[B]						
Per capita	17,002	2,880	15,649	2,688	15,903	2,578
Median household	34,504	6,369	32,246	5,504	32,047	5,472
Percent Below Poverty by age group (%)[B]						
<=5 years	0.32	0.20	0.30	0.20	0.34	0.22
6-11	1.85	1.03	1.97	0.87	2.05	0.93
12-17	1.61	0.82	1.65	0.72	1.78	0.81
18-64	8.04	2.81	8.28	2.58	8.67	2.83
65-74	0.81	0.47	0.93	0.41	0.93	0.43
>=75	1.00	0.56	1.17	0.70	1.17	0.59
Percent Above Poverty by age group (%)[B]						
<=5 years	1.10	0.29	1.08	0.31	1.05	0.30
6-11	6.93	1.10	6.93	0.93	6.72	1.00
12-17	7.34	1.15	7.55	1.03	7.36	1.03
18-64	52.79	4.48	52.48	4.29	51.40	4.43
65-74	6.42	2.16	6.47	1.29	6.62	1.67
>=75	4.80	1.80	4.52	1.31	4.97	1.44

Households with income assistance (%)[B]						
Public assistance	2.81	1.20	2.89	1.16	3.07	1.18
Social Security	5.70	2.48	6.20	2.17	6.39	2.51
Transportation to work (%)[B]						
Own car/truck/van	93.96	2.05	93.83	2.13	93.82	2.24
Public transportation	0.48	0.65	0.42	0.64	0.37	0.56
Bicycle	0.12	0.15	0.07	0.12	0.10	0.14
Motorcycle	0.09	0.12	0.11	0.15	0.09	0.13
Walk	1.92	1.26	1.92	1.31	2.12	1.50
At home	2.55	1.18	2.69	1.42	2.53	1.33
Commute to work by minute range (%)[B]						
<=5 min	13.27	5.17	5.21	2.90	5.70	2.84
5-9	16.64	6.34	12.51	3.64	13.05	4.98
10-14	16.84	5.79	18.09	4.64	15.51	6.28
15-19	13.57	4.66	18.67	4.55	16.74	6.85
20-24	4.75	2.10	15.66	4.15	12.75	4.16
25-29	12.09	4.97	5.44	1.88	4.49	2.08
30-34	2.10	1.50	12.12	4.14	12.23	5.07
35-39	2.29	1.71	1.80	1.24	2.31	1.55
40-44	5.86	4.17	1.92	1.36	2.29	1.55
45-49	3.21	2.15	4.21	2.98	6.40	4.30
60-89	12.09	4.97	2.16	1.04	3.82	2.57
Education (%)[B]						
Less than high school	24.55	7.66	27.15	6.87	27.13	6.83
High school	34.35	5.62	36.37	5.15	35.42	4.99
Some college*	24.76	4.51	23.21	4.36	23.16	4.11
Bachelors	10.85	5.13	8.79	4.64	9.50	4.20
More than bachelors	5.48	3.29	4.49	3.01	4.79	2.85

Notes: **A**: Arkansas Department of Education at the school level; **B**: Census 2000 at the school district.
***** Some college includes associate degree.

Table 2: Obesity prevalence at younger and highest grades by school subtypes (%).

Variable	Younger grade		Highest grade	
	Mean	SD	Mean	SD
Elementary Schools				
K-4 (N=1,026)	17.38	6.28	22.05	6.99
K-5 (N=1,094)	18.86	5.93	23.01	6.82
K-6 (N=1,443)	21.69	6.68	25.06	7.15
Total	19.59	6.61	23.57	7.12
Middle Schools				
5-8 (N=235)	23.13	5.99	22.54	6.06
6-8 (N=124)	23.94	4.91	23.25	4.32
Total	23.41	5.65	22.79	5.52
High Schools				
9-12 (N=585)	21.69	5.77	19.73	5.76
10-12 (N=209)	20.42	5.13	18.05	5.82
Total	21.35	5.63	19.29	5.82
Total (all schools)	20.05	6.51	22.97	7.03

Note: The prevalence by different weight categories at grade level are reported by the Arkansas Center for Health Improvement (ACHI), Little Rock, AR.

Table 3: Effect of obesity prevalence at highest grade on the prevalence among younger grades. N=4,714

School	OLS	LSDV		Random	Within
		1-way FE	*2-way FE*		
Highest graders	0.13*** (0.00)	0.05*** (0.00)	0.05*** (0.00)	0.09*** (0.00)	0.05*** (0.00)
R-sq	0.212	0.833	0.855		0.072

Note: * p<0.10; ** p<0.05; and *** p<0.01. p-value in parenthesis.
All variables listed in Table 1 were included in each of the regressions except that one dummy variable in each dummy variable set was excluded.
LSDV (Least Squares Dummy Variables): 1-way FE includes cohort fixed effects; and 2-way FE includes cohort and year fixed effects.
Panel Methods: 'Random' effects estimator assumes no correlation between the unobserved individual-level intercept and the variables of interest. 'Within' estimator takes deviation from individual means.

Table 4: Effect of obesity prevalence at highest grade on the prevalence among younger grades by school type (in percent). (Each school type is an independent regression.)

School	OLS	LSDV		Random	Within
		1-way FE	*2-way FE*		
Elementary (N=4,919)	0.16*** (0.00)	0.04*** (0.00)	0.05*** (0.00)	0.10*** (0.00)	0.04*** (0.00)
R-sq	0.208	0.812	0.805		0.081
Middle (N=357)	0.07 (0.22)	0.03 (0.50)	0.02 (0.64)	0.06 (0.21)	0.03 (0.50)
R-sq	0.367	0.835	0.840		0.103
High (N=794)	0.18*** (0.00)	0.07 (0.12)	0.06 (0.20)	0.12*** (0.00)	0.07 (0.12)
R-sq	0.377	0.928	0.930		0.223

Note: * p<0.10; ** p<0.05; and *** p<0.01. p-value in parenthesis.
All variables listed in Table 1 were included in each of the regressions except that one dummy variable in each dummy variable set was excluded.
LSDV (Least Squares Dummy Variables): 1-way FE includes cohort fixed effects; and 2-way FE includes cohort and year fixed effects.
Panel Methods: 'Random' effects estimator assumes no correlation between the unobserved individual-level intercept and the variables of interest. 'Within' estimator takes deviation from individual means.

Table 5: Effect of obesity prevalence at highest grade on the prevalence among younger grades in elementary schools. (Each subtype is an independent regression.)

School	OLS	LSDV		Random	Within
		1-way FE	*2-way FE*		
K-4 (N=1,442)	0.16*** (0.00)	0.10*** (0.00)	0.10*** (0.00)	0.13*** (0.00)	0.10*** (0.00)
R-sq	0.335	0.756	0.799		0.086
K-5 (N=1,450)	0.12*** (0.00)	0.01 (0.63)	0.00 (0.88)	0.08** (0.00)	0.01 (0.63)
R-sq	0.168	0.831	0.849		0.094
K-6 (N=2,027)	0.08*** (0.00)	0.05* (0.06)	0.05** (0.03)	0.06*** (0.00)	0.05* (0.06)
R-sq	0.136	0.804	0.838		0.108

Note: * p<0.10; ** p<0.05; and *** p<0.01. p-value in parenthesis.
All variables listed in Table 1 were included in each of the regressions except that one dummy variable in each dummy variable set was excluded.
LSDV (Least Squares Dummy Variables): 1-way FE includes cohort fixed effects; and 2-way FE includes cohort and year fixed effects.
Panel Methods: 'Random' effects estimator assumes no correlation between the unobserved individual-level intercept and the variables of interest. 'Within' estimator takes deviation from individual means.

Table 6: Effect of obesity prevalence at highest grade on the prevalence among younger grades in middle schools. (Each subtype is an independent regression.)

School	OLS	LSDV		Random	Within
		1-way FE	*2-way FE*		
5-8 (N=233)	0.04 (0.60)	0.05 (0.34)	0.04 (0.48)	0.06 (0.26)	0.05 (0.34)
R-sq	0.450	0.848	0.851		0.141
6-8 (N=124)	-0.15 (0.23)	-0.09 (0.48)	-0.06 (0.63)	-0.11 (0.33)	-0.09 (0.48)
R-sq	0.607	0.823	0.842		0.147

Note: * p<0.10; ** p<0.05; and *** p<0.01. p-value in parenthesis.
All variables listed in Table 1 were included in each of the regressions except that one dummy variable in each dummy variable set was excluded.
LSDV (Least Squares Dummy Variables): 1-way FE includes cohort fixed effects; and 2-way FE includes cohort and year fixed effects.
Panel Methods: 'Random' effects estimator assumes no correlation between the unobserved individual-level intercept and the variables of interest. 'Within' estimator takes deviation from individual means.

Table 7: Effect of obesity prevalence at highest grade on the prevalence among younger grades in high schools. (Each subtype is an independent regression.)

School	OLS	LSDV		Random	Within
		1-way FE	*2-way FE*		
9-12 (N=585)	0.11** (0.01)	0.04 (0.39)	0.03 (0.59)	0.08** (0.04)	0.04 (0.39)
R-sq	0.388	0.924	0.928		0.232
10-12 (N=209)	0.13 (0.14)	0.17* (0.08)	0.16* (0.10)	0.12* (0.10)	0.17* (0.08)
R-sq	0.587	0.946	0.946		0.282

Note: * p<0.10; ** p<0.05; and *** p<0.01. p-value in parenthesis.
All variables listed in Table 1 were included in each of the regressions except that one dummy variable in each dummy variable set was excluded.
LSDV (Least Squares Dummy Variables): 1-way FE includes cohort fixed effects; and 2-way FE includes cohort and year fixed effects.
Panel Methods: 'Random' effects estimator assumes no correlation between the unobserved individual-level intercept and the variables of interest. 'Within' estimator takes deviation from individual means.

Table 8: Effect of current obesity prevalence at highest grade on past changes and future changes in obesity prevalence among younger grades by school types. (Each school type is an independent regression.)

School	OLS	LSDV		Random	Within
		1-way FE	*2-way FE*		
Past changes in the LHS variable [A]					
Elementary (N=1,681)	0.06*** (0.00)	0.08* (0.08)	0.07* (0.10)	0.06*** (0.00)	0.08* (0.08)
Middle (N=185)	0.01 (0.95)	0.02 (0.93)	-0.01 (0.96)	0.01 (0.95)	0.02 (0.93)
High (N=266)	0.07 (0.30)	-0.27* (0.10)	-0.27 (0.11)	0.07 (0.30)	-0.27* (0.10)
All Schools (N=2,132)	0.10*** (0.00)	0.07 (0.10)	0.06 (0.14)	0.10*** (0.00)	0.07 (0.10)
Future changes in the LHS variable [B]					
Elementary (N=1,681)	0.01 (0.53)	0.04 (0.38)	0.04 (0.35)	0.01 (0.53)	0.04 (0.38)
Middle (N=185)	-0.04 (0.65)	0.13 (0.57)	0.16 (0.39)	-0.04 (0.65)	0.13 (0.57)
High (N=266)	0.08 (0.19)	0.19 (0.30)	0.19 (0.31)	0.08 (0.18)	0.19 (0.30)
All Schools (N=2,132)	0.05** (0.01)	0.04 (0.30)	0.05 (0.25)	0.05** (0.01)	0.04 (0.30)

Note: * $p<0.10$; ** $p<0.05$; and *** $p<0.01$. p-value in parenthesis.
A indicates regression of $Y_{i(t-‘t-1’)}$ on $Y_{jt\cdot}$, where *i* is the younger grade and *j* is the highest grade in a school.
B indicates regression of $Y_{i(‘t+1’-t)}$ on $Y_{jt\cdot}$, where *i* is the younger grade and *j* is the highest grade in a school.
All variables listed in Table 1 were included in each of the regressions except that one dummy variable in each dummy variable set was excluded.
LSDV (Least Squares Dummy Variables): 1-way FE includes cohort fixed effects; and 2-way FE includes cohort and year fixed effects.
Panel Methods: ‘Random’ effects estimator assumes no correlation between the unobserved individ`ual-level intercept and the variables of interest. ‘Within’ estimator takes deviation from individual means.

Table 9A: Effect of obesity and overweight prevalence at highest grade on obesity prevalence among younger grades by school subtype in elementary schools. (Each subtype is an independent regression.)

School	OLS	LSDV		Random	Within
		1-way FE	*2-way FE*		
K-4					
Obese	0.15*** (0.00)	0.10*** (0.00)	0.10*** (0.00)	0.12*** (0.00)	0.10*** (0.00)
Overweight	0.08** (0.04)	0.03 (0.42)	0.01 (0.79)	0.06 (0.12)	0.03 (0.42)
K-5					
Obese	0.12*** (0.00)	0.01 (0.62)	0.00 (0.87)	0.06** (0.02)	0.01 (0.62)
Overweight	-0.04 (0.26)	0.01 (0.76)	0.02 (0.55)	-0.02 (0.56)	0.01 (0.76)
K-6					
Obese	0.09*** (0.00)	0.05* (0.06)	0.05** (0.03)	0.07*** (0.00)	0.05* (0.06)
Overweight	0.09** (0.01)	-0.01 (0.82)	0.00 (0.94)	0.04 (0.20)	-0.01 (0.82)
Elementary (all subtypes pooled)					
Obese	0.16*** (0.00)	0.05*** (0.00)	0.05*** (0.00)	0.10*** (0.00)	0.05*** (0.00)
Overweight	0.09*** (0.00)	0.01 (0.64)	0.01 (0.60)	0.04** (0.02)	0.01 (0.64)

Note: * p<0.10; ** p<0.05; and *** p<0.01. p-value in parenthesis.
All variables listed in Table 1 were included in each of the regressions except that one dummy variable in each dummy variable set was excluded.
LSDV (Least Squares Dummy Variables): 1-way FE includes cohort fixed effects; and 2-way FE includes cohort and year fixed effects.
Panel Methods: 'Random' effects estimator assumes no correlation between the unobserved individual-level intercept and the variables of interest. 'Within' estimator takes deviation from individual means.

Table 9B: Effect of obesity and overweight prevalence at highest grade on obesity prevalence among younger grades by school subtype in middle schools. (Each subtype is an independent regression.)

School	OLS	LSDV		Random	Within
		1-way FE	*2-way FE*		
5-8					
Obese	0.03 (0.74)	0.05 (0.39)	0.04 (0.51)	0.04 (0.43)	0.05 (0.39)
Overweight	-0.06 (0.54)	-0.10 (0.16)	-0.08 (0.24)	-0.09 (0.19)	-0.10 (0.16)
6-8					
Obese	-0.15 (0.24)	-0.09 (0.49)	-0.06 (0.64)	-0.11 (0.34)	-0.09 (0.49)
Overweight	0.06 (0.53)	0.11 (0.25)	0.14 (0.14)	0.08 (0.37)	0.11 (0.25)
Middle (all subtypes pooled)					
Obese	0.07 (0.22)	0.03 (0.53)	0.02 (0.66)	0.06 (0.22)	0.03 (0.53)
Overweight	0.02 (0.80)	-0.04 (0.44)	-0.03 (0.64)	-0.02 (0.77)	-0.04 (0.44)

Note: * p<0.10; ** p<0.05; and *** p<0.01. p-value in parenthesis.
All variables listed in Table 1 were included in each of the regressions except that one dummy variable in each dummy variable set was excluded.
LSDV (Least Squares Dummy Variables): 1-way FE includes cohort fixed effects; and 2-way FE includes cohort and year fixed effects.
Panel Methods: 'Random' effects estimator assumes no correlation between the unobserved individual-level intercept and the variables of interest. 'Within' estimator takes deviation from individual means.

Table 9C: Effect of obesity and overweight prevalence at highest grade on obesity prevalence among younger grades by school subtype in high schools. (Each subtype is an independent regression.)

School	OLS	LSDV		Random	Within
		1-way FE	*2-way FE*		
9-12 (N=585)					
Obese	0.12** (0.01)	0.05 (0.34)	0.03 (0.51)	0.08** (0.04)	0.05 (0.34)
Overweight	0.04 (0.44)	-0.06 (0.21)	-0.07 (0.12)	-0.01 (0.88)	-0.06 (0.21)
10-12 (N=209)					
Obese	0.11 (0.22)	0.17* (0.08)	0.17* (0.10)	0.12 (0.10)	0.17* (0.08)
Overweight	0.09 (0.44)	0.05 (0.71)	0.05 (0.69)	0.09 (0.37)	0.05 (0.71)
High (all subtypes pooled)					
Obese	0.18*** (0.00)	0.07 (0.11)	0.06 (0.18)	0.12*** (0.00)	0.07 (0.11)
Overweight	0.06 (0.14)	-0.05 (0.26)	-0.06 (0.16)	0.02 (0.64)	-0.05 (0.26)

Note: * p<0.10; ** p<0.05; and *** p<0.01. p-value in parenthesis.
All variables listed in Table 1 were included in each of the regressions except that one dummy variable in each dummy variable set was excluded.
LSDV (Least Squares Dummy Variables): 1-way FE includes cohort fixed effects; and 2-way FE includes cohort and year fixed effects.
Panel Methods: ‘Random’ effects estimator assumes no correlation between the unobserved individual-level intercept and the variables of interest. ‘Within’ estimator takes deviation from individual means.