Disentangling the Relative Influence of Schools and Neighborhoods on Adolescents' Risk for Depressive Symptoms

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Depression is one of the most serious public health problems among adolescents in the United States. Large epidemiological studies estimate that 12% of young people meet lifetime diagnostic criteria for major depression or dysthymia[1] and that 29% of high school students report having felt sad or hopeless nearly every day during the preceding 2 weeks.[2] Given that adolescent-onset depression is associated with many short- and long-term consequences, including suicidal thoughts and behaviors[3,4]; cigarette, alcohol, and drug use[5–7]; and recurrent episodes of depression in adulthood,[8,9] there is an urgent need to understand the etiology of depression in adolescence.

Interest in the social determinants of depression—or how features of the broader social context in which adolescents are embedded affect their risk for depression—has increased in the past decade. Neighborhood social environments have been primarily examined to date.[10–14] Research in this area suggests that a neighborhood's racial/ethnic and socioeconomic composition and culture (e.g., levels of social cohesion, norms related to relationships between neighbors) are associated with individual mental health outcomes, even after individual-level factors have been taken into account. Although schools are gaining more interest from public health researchers,[15,16] research on the role of schools in depression is lacking outside of a small number of studies. These studies, which have primarily focused on school connectedness and school socioeconomic status (SES), have shown that higher levels of each of these elements are associated with lower levels of depressive symptoms among students.[17–25] In addition, most school-related studies have focused on individual-level rather than multilevel associations.[26–32]

Not only are schools understudied on their own, but their role in relation to neighborhoods

Objectives. Although schools and neighborhoods influence health, little is known about their relative importance, or the influence of one context after the influence of the other has been taken into account. We simultaneously examined the influence of each setting on depression among adolescents.

Methods. Analyzing data from wave 1 (1994–1995) of the National Longitudinal Study of Adolescent Health, we used cross-classified multilevel modeling to examine between-level variation and individual-, school-, and neighborhood-level predictors of adolescent depressive symptoms. Also, we compared the results of our cross-classified multilevel models (CCMMs) with those of a multilevel model wherein either school or neighborhood was excluded.

Results. In CCMMs, the school-level random effect was significant and more than 3 times the neighborhood-level random effect, even after individual-level characteristics had been taken into account. Individual-level indicators (e.g., race/ethnicity, socioeconomic status) were associated with depressive symptoms, but there was no association with either school- or neighborhood-level fixed effects. The between-level variance in depressive symptoms was driven largely by schools as opposed to neighborhoods.

Conclusions. Schools appear to be more salient than neighborhoods in explaining variation in depressive symptoms. Future work incorporating cross-classified multilevel modeling is needed to understand the relative effects of schools and neighborhoods. (*Am J Public Health.* 2015;105:732–740. doi:10.2105/AJPH.2014.302374)

is also poorly understood.[33] Studies involving cross-classified multilevel modeling techniques, which explicitly allow researchers to disentangle the unique effects on health of multiple non-nested contexts (e.g., school and neighborhood environments),[34,35] are rare. This is especially true for mental health outcomes. As a result, it remains unclear whether each context is important independent of the other and, if so, whether schools or neighborhoods are equally important determinants of adolescent depression or one context is more salient than the other.

A case could be made for the importance of both schools and neighborhoods. Schools are likely to be important determinants of depression because they serve more than 95% of the nation's young people for approximately 6 hours per day (or upward of 40% of students' waking time during the school year) and at least

11 continuous years of their lives.[36] Schools are also well-defined social institutions providing access to a range of supportive relationships that promote mental health.[30,37,38] Neighborhoods, by contrast, may be important because they are the setting where unstructured social activity occurs outside of school and during the summer.[39,40] Neighborhoods may also have a more direct influence on parents' capacity to raise their children through shaping of community norms, supervision and monitoring, collective efficacy, and reductions in the burdens and stressors associated with caregiving.[41,42]

Studies that examine the salience of schools relative to neighborhoods (and vice versa) are needed, given that schools and neighborhoods have increasingly become nonnested contexts in the United States. Indeed, a growing number

of young people are attending schools outside of their neighborhoods as a result of the popularity of school choice (e.g., charter schools, federal vouchers to attend private school) and the desire to close low-performing schools.[43,44] Thus, in the case of many young people, schools and neighborhoods are no longer hierarchically nested; for example, adolescents may attend non-neighborhood-based schools that have demographic features different from those of their neighborhood of residence.

Our objective was to address these gaps in the literature by providing an understanding of the relative importance of neighborhoods and schools in levels of youth depressive symptoms. Specifically, we set out to determine the unique proportion of variance in depressive symptoms attributable to schools and neighborhoods (i.e., the random effects of each context) and examine the association between youth depression and sociodemographic characteristics (e.g., SES, race/ethnicity) at the individual, school, and neighborhood levels (i.e., fixed effects).

METHODS

Our data came from wave 1 of the National Longitudinal Study of Adolescent Health (Add Health), one of the few nationally representative longitudinal surveys of US adolescents that examines health and health-related behaviors and includes information about both school and neighborhood environments.[45] Adolescents in grades 7 to 12 were recruited through school-based sampling and were first interviewed in 1994 to 1995 (wave 1).[18] A systematic random sample of high schools along with feeder schools (i.e., middle schools whose students matriculate at the selected high school) was selected. A total of 134 schools (79%) participated. An in-school survey was completed by 90 118 students. A random sample of these students (as well as all students who were eligible to complete the in-school survey but were absent on the day of administration) were invited to complete a more detailed in-home interview, and 20 745 students did so (more than 75% of those asked to participate). In addition, 17 670 caregivers (for 85% of in-home respondents) provided information at wave 1.

Our cross-sectional analyses were based on an analytic sample of 16 172 students nested

in 128 schools (a median of 103.5 students per school, ranging from 18 to 1018) and 2118 neighborhoods (a median of 2 students per neighborhood, ranging from 1 to 262; neighborhoods were defined according to census tracts). This analytic sample was derived after students from the sample that was not nationally representative (i.e., students who attended schools sampled for genetic analyses) and students from schools that did not provide demographic data had been eliminated (n = 660). We also excluded adolescents who were missing data on the outcome measure (n = 38) or predictors and covariates (n = 1404). We restricted our analysis to adolescents who were White, Black, or Hispanic, given that students in other racial/ethnic groups were not sufficiently represented in Add Health to obtain robust group estimates (less than 1% of the students were Native American, 6% were Asian, and 6% were from other racial/ethnic backgrounds).

Although Add Health is a longitudinal study, we pursued a cross-sectional analysis here because the majority of respondents resided in the same neighborhood and school in wave 2 as they did in wave 1 and because waves 3 and 4 were conducted when most respondents had graduated from high school.

Measures

Our outcome measure was depressive symptoms. Symptoms were assessed at wave 1 with a 19-item adaptation of the Center for Epidemiological Studies Depression Scale (CES-D),[46] a widely used instrument that captures symptoms of depression. Adolescents reported how often they had experienced each symptom in the preceding week; responses ranged from never or rarely to most or all of the time. The adapted CES-D had good internal consistency reliability in this sample (Cronbach $\alpha = 0.87$). CES-D scores were slightly skewed toward lower values; because skew (1.15) and kurtosis (1.89) values were within reasonable limits and linear regression is robust to minor violations of normality,[47,48] we did not conduct any transformations of the data.

The first of our predictors was SES. Measures focusing on parent education and parental receipt of public assistance were used to obtain data on SES at the individual, school, and neighborhood levels. At the individual

level, we used items from the caregiver interview (or, when this information was not available, the in-home version of the youth interview) to determine the highest level of parent education (of the resident mother, resident father, or resident stepfather or partner). We used responses to these items to create a binary variable (1 = at least 1 parent graduated from college, 0 = neither parent graduated from college). We also determined parent receipt of public assistance at the individual level from data available in either the in-school youth or in-home caregiver survey (1 = parent currently receives public assistance, 0 = no current assistance).

We calculated school-level SES predictors from the proportion of students within each school with a parent receiving public assistance and the proportion of students with at least 1 parent who had earned a college degree. Because information on school-level SES was not directly available, aggregation of individual-level data was required. At the neighborhood level, we used data from the 1990 US census to create SES measures indicating the proportion of residents within each neighborhood who had received public assistance or had a college degree.

Our other predictor, race/ethnicity, was also measured at the individual, school, and neighborhood levels. At the individual level, we used a self-reported measure of race/ethnicity (1 = non-Hispanic White, 2 = non-Hispanic Black, 3 = Hispanic). We limited our analyses to these groups given the smaller number of participants from other racial/ethnic groups. We created a school-level measure by calculating the proportion of students within each school who, according to data from the in-school interview, were non-Hispanic White. At the neighborhood level, 1990 census data were used to create a measure of the proportion of residents in the neighborhood who were non-Hispanic White.

Finally, our adjusted models controlled for the covariates of age (continuous) and gender (male = 0, female = 1).

Analysis

Our analyses proceeded in 5 steps. Initially, we estimated 3 sets of null or random-intercept-only multilevel models: a school-only multilevel model (MLM) in which

adolescents were clustered within schools, a neighborhood-only MLM in which adolescents were clustered within neighborhoods, and a cross-classified multilevel model (CCMM) in which adolescents were grouped simultaneously into both a school and a neighborhood. These null models (models 1A–1C) allowed us to partition the variance in depressive symptoms into within and between components and to estimate an intraclass correlation coefficient (ICC; i.e., the proportion of variation in the outcome that was due to differences across schools or neighborhoods rather than differences across students). The coefficients in the null CCMMs are as follows: b refers to the overall mean outcome y across all schools and neighborhoods, $u0j$ refers to the random effect for schools, $u0k$ refers to the random effect for neighborhoods, and $u0ijk$ refers to the random effect for the combination of j school and k neighborhood. Similar to a traditional multilevel model, the CCMM variance parameters are assumed to be independent of each other and normally distributed, with a mean of 0 and a variance that is estimated.

Next, we estimated a CCMM that contained individual-level predictors and covariates (model 2) with the random effects of both schools and neighborhoods simultaneously taken into account. By including individual-level variables, we were able to evaluate the extent to which the between-level variance estimates for both schools and neighborhoods (i.e., random effect parameters) were due to the observed composition (i.e., the characteristics of individuals in a given school or neighborhood). We then added to model 2 the school-level variables (model 3) and neighborhood-level predictors (model 4). Finally, we fit a CCMM containing all individual-, school-, and neighborhood-level variables of interest (model 5).

We conducted all analyses in MLwiN version 2.26 (Centre for Multilevel Modeling, London, England) with Bayesian estimation procedures, implemented via Markov chain Monte Carlo methodology.[49] Parameter estimates and 95% credible intervals (the confidence intervals generated with Bayesian procedures) are presented for fixed-effect parameters. For random-effect parameters, we present variance estimates and 95% credible intervals. We examined residual plots at each

level of analysis to evaluate model diagnostics related to variance parameters; this enabled us to test model assumptions and to detect outliers and influence points related to model fit. Two-tailed P values are presented for fixed-effect parameters and 1-tailed values for residual variance terms, given that values less than zero are implausible.

We used unweighted data in conducting our analyses, as weighting techniques for cross-classified multilevel modeling have not been established.[50] A nonweighted analysis was appropriate because our emphasis was on conducting tests of association rather than deriving nationally representative estimates, and we adjusted our analyses for sample characteristics and thus reduced the heterogeneity of the sample.[51]

RESULTS

The sample was predominantly White (58%), was balanced according to gender (51% female), and consisted largely of respondents in midadolescence (mean age = 15.6 years; SD = 1.7). The sample was modestly disadvantaged; 70% of adolescents had no parent with a college degree, and 10% had at least 1 parent who was receiving public assistance. Adolescents' average depression score was 11.1 (SD = 7.5; minimum = 0, maximum = 56). The average depressive symptom score was similar across neighborhoods (neighborhood mean = 11.2; SD = 6.1) and schools (school mean = 10.8; SD = 1.6), yet there was marked variation within schools and neighborhoods (Figure 1).

Average SES was similar across schools and neighborhoods. Specifically, the school-specific percentage of parents on public assistance was 10.4% (SD = 9.4%; minimum = 0%, maximum = 45.4%), and the neighborhood-specific percentage of residents on public assistance was 10.7% (SD = 10.0%; minimum = 0%, maximum = 67.5%). Similarly, the school-specific percentage of parents who had less than a college education was 68.3% (SD = 16.9%; minimum = 8.8%, maximum = 94.5%), as compared with the neighborhood-specific percentage of 76.6% (SD = 14.6%; minimum = 17.5%, maximum = 100%).

Table 1 presents the results of the school-only and neighborhood-only MLMs and the

CCMM. In these null models, with schools and neighborhoods examined in separate MLMs (model 1), the random effects for schools ($\sigma_{u0j}^2 = 2.05$) and neighborhoods ($\sigma_{u0k}^2 = 1.84$) were similar. ICC values were comparable at the school (3.6%) and neighborhood (3.2%) levels. However, the CCMM showed that the between-level variance in depressive symptoms was driven largely by schools ($\sigma_{u0j}^2 = 1.69$) as opposed to neighborhoods ($\sigma_{u0k}^2 = 0.45$) (school ICC = 3.0%, neighborhood ICC = 0.8%).

Adding individual-level covariates to the CCMM (model 2) attenuated the between-level variance for schools ($\sigma_{u0j}^2 = 0.70$) and neighborhoods ($\sigma_{u0k}^2 = 0.19$), but the individual-level residual variance was largely unchanged (school ICC = 1.3%, neighborhood ICC = 0.4%). This decline suggests that, although the change was more striking in neighborhoods, the between-level variation in depressive symptoms was due largely to compositional effects (i.e., characteristics of adolescents in these contexts). The results of this model also suggest that depressive symptom scores were higher among female students (b = 1.97), Black (b = 1.00) and Hispanic (b = 1.52) students, older students (b = 0.40), students who had a parent on public assistance (b = 1.70), and students with at least 1 parent who had a college degree (b = −1.46).

Table 2 presents the results of the CCMMs including school- and neighborhood-level predictors. In model 3, which added the school-level covariates to model 2, the residual variance terms at the school ($\sigma_{u0j}^2 = 0.65$), neighborhood ($\sigma_{u0k}^2 = 0.20$), and student ($\sigma_{u0ijk}^2 = 52.82$) levels were largely unchanged. Consistent with this finding, we also did not detect any statistically significant fixed effects for the school-specific percentage of students with a parent receiving public assistance (b = 0.02), the percentage with at least 1 parent who had a college degree (b = −0.01), or the percentage who were White (b = −0.01).

The results for model 4, which added the neighborhood-level covariates to model 2, were similar to those of model 3. The residual variance terms at the school ($\sigma_{u0j}^2 = 0.73$), neighborhood ($\sigma_{u0k}^2 = 0.15$), and student ($\sigma_{u0ijk}^2 = 52.80$) levels were largely unchanged. Similarly, no statistically

a

b
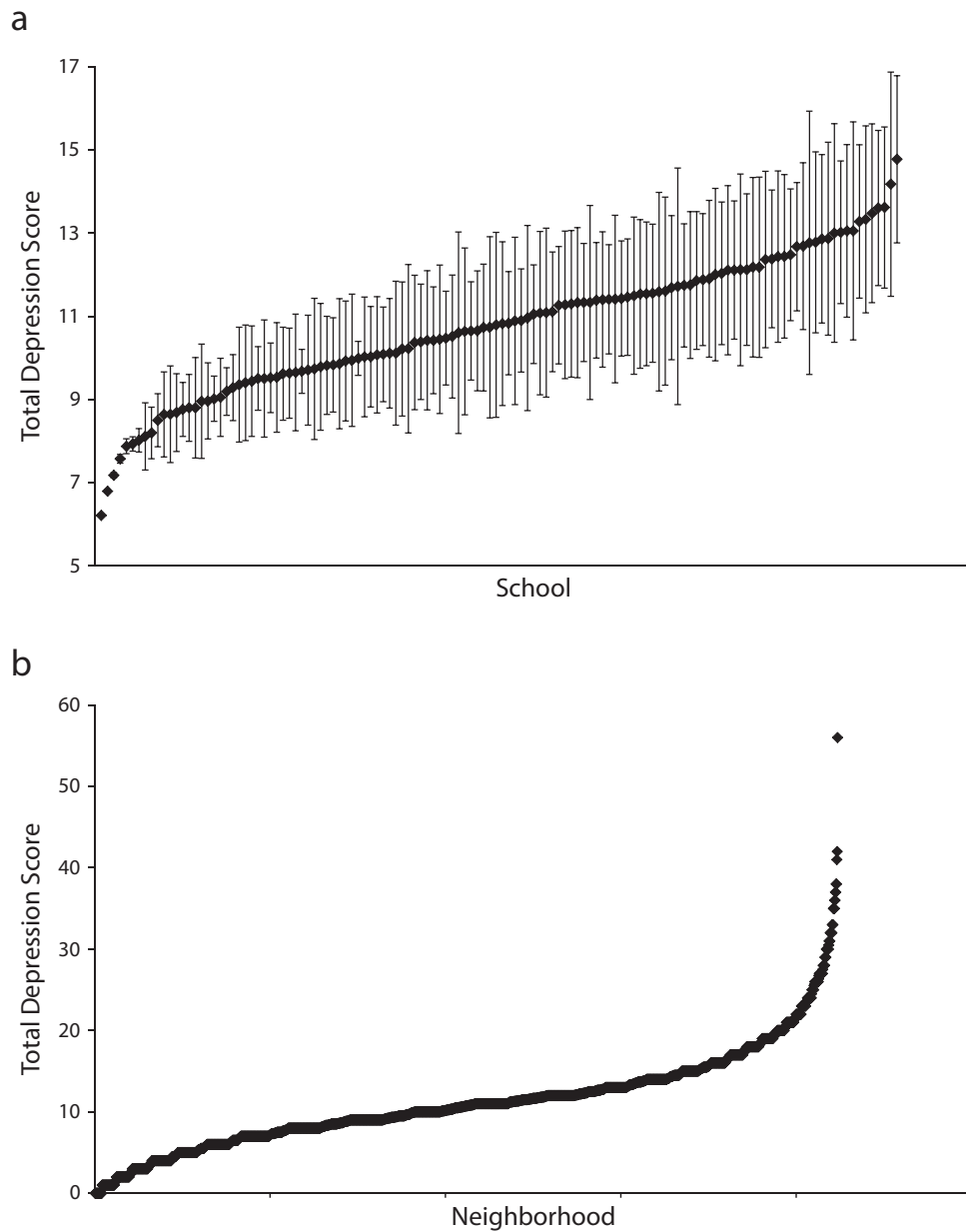
Note. Dots represent the mean within-school total depression scores. Ninety-five percent bounds around the means (based on the standard deviations of within-school total depression scores) are also presented; these values are excluded for neighborhoods owing to the high number of neighborhoods present in the data. Values are sorted from left to right by lowest school or neighborhood mean. Average depressive symptom scores across schools ranged from 6.2 to 14.8. Average depressive symptoms scores across neighborhoods ranged from 0 to 56.

FIGURE 1—Distribution of depressive symptoms within and between (a) schools (n = 128) and (b) neighborhoods (n = 2118): National Longitudinal Study of Adolescent Health, 1994–1995.

significant fixed effects were detected for the neighborhood-specific percentage of residents who received public assistance (b = 0.02), the percentage who had a college degree (b = −0.01), or the percentage who were White (b = −0.00). The results of model

5, which contained all of the individual, school, and neighborhood factors, were similar to the results of the previous models, with only individual fixed effects being significant and the school random effect remaining significant.

DISCUSSION

In this study, we used cross-classified multi-level modeling to disentangle the effects of schools and neighborhoods on adolescents' risk for depression. Two major findings emerged

TABLE 1—Nested Models Showing the Associations Between Predictors and Depressive Symptoms: National Longitudinal Study of Adolescent Health, 1994–1995

	Model 1			Model 2: CCMM
	School-Only MLM	Neighborhood-Only MLM	CCMM	
	Fixed-effect estimates			
Intercept (SE)	11.2* (0.09)	11.1* (0.08)	10.8* (0.14)	3.6* (0.61)
Individual-level predictor				
Age	. . .	. . .	. . .	0.40* (0.32, 0.47)
Female	. . .	. . .	. . .	1.97* (1.74, 2.21)
Public assistance	. . .	. . .	. . .	1.70* (1.31, 2.09)
College degree (parent)	. . .	. . .	. . .	–1.46* (-1.72, –1.20)
White (Ref)	. . .	. . .	. . .	1.00
Black	. . .	. . .	. . .	1.00* (0.66, 1.35)
Hispanic	. . .	. . .	. . .	1.52* (1.13, 1.91)
	Random-effect estimates			
Neighborhood (95% CI)	. . .	1.84* (1.32, 2.37)	0.45* (0.10, 0.79)	0.19* (-0.02, 0.39)
School (95% CI)	2.05* (1.5, 2.61)	. . .	1.69* (1.10, 2.28)	0.70* (0.37, 1.02)
Individual (95% CI)	54.65* (53.43, 55.86)	55.04* (53.81, 56.27)	54.68* (53.48, 55.89)	52.81* (51.64, 53.99)
	Fit statistics			
Deviance information criterion[a]	. . .	. . .	110 788	110 169
	Intraclass correlation coefficient[b] estimates, %			
Neighborhood	. . .	3.2	0.8	0.4
School	3.6	. . .	3.0	1.3

Note. CCMM = cross-classified multilevel model; CI = credible interval; MLM = multilevel model. The sample size was n = 16 172. For fixed-effect estimates, entries are parameter estimates (b) and credible intervals. All other entries are estimates (of variance) and credible intervals.
[a]A measure of model fit reported only for cross-classified multilevel models. Higher values indicate a poorer fitting model.
[b]Proportion of variance in the outcome attributable to neighborhoods (after adjustment for schools) or to schools (after adjustment for neighborhoods).
*P < .05.

from our investigation. First, we found that schools appeared to drive the between-level variance in depressive symptoms more than neighborhoods. After individual-level (or compositional) characteristics had been taken into account, the school-level random effect was statistically significant and more than 3 times the neighborhood-level random effect. These findings suggest that schools may be more salient than neighborhoods with respect to influencing depressive symptoms among adolescents.

Although the magnitude of these school effects (e.g., ICC estimates) was small, with the majority of the variation in depressive symptoms being due to differences between adolescents, our findings suggest that schools contribute to variations in levels of depressive symptoms. Therefore, schools, including school-level predictors (e.g., school-based interventions), may be an important context for reducing the population-level burden of

depression. Our findings also underscore the need to use cross-classified multilevel modeling, as the results we uncovered would have been missed had we used traditional multilevel modeling.[34,52]

Second, we found that only student-level factors (i.e., gender, race/ethnicity, age, parental SES) were significantly associated with depressive symptoms. None of the school-level predictors (the percentage of students with a parent receiving public assistance, the percentage with at least 1 parent who had a college degree, and the percentage who were White) or neighborhood-level predictors (the percentage of residents on public assistance, the percentage without a college degree, and the percentage who were White) were associated with depressive symptoms in any of our models.

Our results differed from previous findings,[10–14] including studies in which Add Health data were used to examine either the

school or neighborhood context alone via a multilevel model.[24,53–56] These differences are unsurprising given that substantially different approaches have been used to assess such questions in Add Health and other data sets (e.g., different predictors, covariates, and samples). However, even after conducting additional cross-classified multilevel modeling analyses to more closely mimic prior Add Health work (e.g., focusing on income as the measure of SES), we still reached the same substantive conclusions (results are available from the authors). Future studies are therefore needed to replicate and extend our findings, with a specific emphasis on comparing the results of MLM analyses with those of CCMM analyses. Future studies are also needed to understand the school-related aspects that may contribute to between-school variation in adolescent depression, given that none of the variables we examined appeared to be large contributors.

TABLE 2—Nested Cross-Classified Multilevel Models Showing the Associations Between Predictors and Depressive Symptoms: National Longitudinal Study of Adolescent Health, 1994–1995

	Model 3 (School-Level Predictors)	Model 4 (Neighborhood-Level Predictors)	Model 5 (School- and Neighborhood-Level Predictors)
	Fixed-effect estimates		
Intercept (SE)	3.91* (0.8)	4.01* (0.8)	3.98* (0.9)*
Individual-level predictor			
Age	0.40* (0.33, 0.48)	0.39* (0.32, 0.47)	0.40* (0.32, 0.48)
Female	1.97* (1.74, 2.20)	1.97* (1.74, 2.20)	1.97* (1.75, 2.20)
Public assistance	1.63* (1.23, 2.04)	1.60* (1.19, 2.00)	1.57* (1.17, 1.97)
College degree (parent)	−1.41* (−1.68, −1.14)	−1.37* (−1.64, −1.09)	−1.36* (−1.62, −1.09)
White (Ref)	1.00	1.00	1.00
Black	0.84* (0.46, 1.22)	0.72* (0.30, 1.13)	0.68* (0.27, 1.09)
Hispanic	1.37* (0.95, 1.79)	1.41* (1.02, 1.81)	1.33* (0.92, 1.74)
School-level predictor			
Public assistance, %	0.02 (−0.02, 0.05)	. . .	0.01 (−0.03, 0.04)
College degree, %	−0.01 (−0.02, 0.01)	. . .	0.00 (−0.02, 0.02)
White, %	−0.01 (−0.02, 0.00)	. . .	−0.01 (−0.02, 0.01)
Neighborhood-level predictor			
Public assistance, %	. . .	0.02 (0.00, 0.05)	0.02 (−0.01, 0.05)
College degree, %	. . .	−0.01 (−0.02, 0.00)	−0.01 (−0.03, 0.00)
White, %	. . .	0.00 (0.00, 0.01)	0.00 (−0.01, 0.01)
	Random-effect estimates		
Neighborhood (95% CI)	0.20* (−0.02, 0.42)	0.15 (−0.03, 0.33)	0.15 (−0.02, 0.31)
School (95% CI)	0.65* (0.33, 0.96)	0.73* (0.40, 1.05)	0.73* (0.38, 1.08)
Individual (95% CI)	52.82* (51.6, 54.0)	52.80* (51.62, 53.98)	52.80* (51.63, 53.98)
	Fit statistics		
Deviance information criterion[a]	110 168	110 157	110 158
	Intraclass correlation coefficient[b] estimates, %		
Neighborhood	0.4	0.3	0.3
School	1.2	1.4	1.4

Note. CI = credible interval. The sample size was n = 16 172. For fixed-effect estimates, entries are parameter estimates (b) and credible intervals. All other entries are estimates (variance) and credible intervals.
[a] A measure of model fit reported only for cross-classified multilevel models. Higher values indicate a poorer fitting model.
[b] Proportion of variance in the outcome attributable to neighborhoods (after adjustment for schools) or to schools (after adjustment for neighborhoods).
*P < .05.

To our knowledge, only 1 group of researchers have used cross-classified multilevel modeling to examine the simultaneous influence of neighborhoods and schools on adolescents' self-reported well-being. In a study of 9107 high school students in New Zealand, Aminzadeh et al. found that 1.16% of the variance in well-being was attributed to neighborhoods after schools had been taken into account, as compared with only 0.14% for schools after neighborhoods had been taken into account.[57] The differences in results between our study and the Aminzadeh et al. study are interesting, particularly given that both studies sampled students via school-based sampling approaches. These differences could be due to numerous factors, including differences in school and neighborhood salience between the United States and New Zealand and differences in school and neighborhood salience between outcomes.

Given the lack of prior research involving cross-classified multilevel modeling, additional studies are needed to disentangle the unique effects of school and neighborhood environments. Knowledge generated from such studies can help guide policymakers in determining where to apply limited funds to most effectively shape young people's development and reduce their risk for mental health problems such as depression.

Why might schools be more important than neighborhoods in shaping adolescent's risk for depression? First, students spend a majority of time outside of their home in schools, and schools involve high levels of adult monitoring of student behavior during the day. Second, schools are no longer solely formal educational institutions; instead, they are settings in which numerous health- and development-promoting interventions take place[58–60] and students acquire knowledge and learn health-promoting

skills in both cognitive and social–emotional domains (e.g., problem solving, coping, cognitive restructuring).[61–63]

Third, schools have formal opportunities, through mental health screening, health services, and educational mandates, to monitor youth behavior and intervene with those at risk.[64,65] Thus, schools may contribute more than neighborhoods to the variance in depressive symptoms because students are exposed to a range of possible risk or protective factors in school that influence the onset of depressive symptoms. Moreover, schools are one of the settings in which depressive symptoms can be more easily addressed once they emerge, as a result of school-based mental health services. Examination of a range of school characteristics, including school-level resources and social climate (e.g., levels of student connectedness to the school), will be important to better understand the impact of schools on adolescents' risk for depression.

Limitations

Our study had several limitations that must be noted when interpreting the results. First, and most important, our analyses were based on a nationally representative sample of adolescents selected via school-based sampling. Whether our findings are an artifact of the sampling strategy remains unknown. It is possible that our results reflect the greater number of individuals per school than per neighborhood. We believe that this is unlikely, however, given that preliminary CCMM analyses we conducted in Add Health to examine other health outcomes did show meaningful effects for neighborhoods (results are available from the authors). Moreover, when we conducted sensitivity analyses in which neighborhoods with fewer than 5 respondents were eliminated, our findings were similar (results are available from the authors). Although these findings are reassuring, simulation studies and studies in which cross-classified multilevel modeling is used in the context of neighborhood-based sampling designs are needed to determine the extent to which sampling influences cross-classified results.

Second, Add Health wave 1 data were collected almost 20 years ago. Although these data are older, Add Health remains the only nationally representative sample of adolescents

in the United States and thus was one of the only large-scale studies available to test our research questions. Third, our outcome measure was based on symptoms of depression during the preceding week rather than diagnostic interviews or depressive symptoms measured over a longer period of time. However, this measure has been widely used in epidemiological studies and has demonstrated good reliability and validity.[46]

Fourth, our use of binary indicators, particularly of SES, may have resulted in some degree of misclassification of respondents and, therefore, residual confounding. However, when we conducted our analyses with continuous measures, the results were similar. Finally, given that we defined neighborhoods according to census tracts, individuals' neighborhoods may have been misclassified. Although census tracts are an imperfect measure to define neighborhoods, they are commonly used in multilevel research.[66] Future studies may wish to expand on traditional neighborhood boundaries and school boundaries and focus their comparisons on activity spaces, or the spaces where students travel during the course of their day-to-day activities.[67]

Conclusions

Despite the limitations just described, our results suggest that schools may have a unique potential to affect, at a population level, the prevalence of depression among adolescents. Furthermore, our study provides a good demonstration of how cross-classified multilevel modeling can answer questions related to differential effects of schools and neighborhoods. Such studies are sorely needed given the dearth of research involving these types of models. Future studies incorporating cross-classified multilevel modeling are necessary to guide investments of limited public health resources and identify in which settings (schools, neighborhoods, or both) public health policies and interventions can have the greatest impact. ∎

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Human Participant Protection

No protocol approval was needed for this study because the analysis involved secondary data.

References

1. Merikangas KR, He S, Burstein M, et al. Lifetime prevalence of mental disorders in U.S. adolescents: results from the National Comorbidity Survey Replication-Adolescent Supplement (NCS-A). *J Am Acad Child Adolesc Psychiatry.* 2010;49(10):980–989.

2. Eaton DK, Kann L, Kinchen S, et al. Youth risk behavior surveillance—United States, 2011. *MMWR Surveill Summ.* 2012;61(SS-4):1–162.

3. Hallfors DD, Waller MW, Ford CA, Halpern CT, Brodish PH, Iritani B. Adolescent depression and suicide risk: association with sex and drug behavior. *Am J Prev Med.* 2004;27(3):224–231.

4. Harrington R. Depression, suicide, and deliberate self-harm in adolescence. *Br Med Bull.* 2001;57(1):47–60.

5. Escobedo LG, Reddy M, Giovino GA. The relationship between depressive symptoms and cigarette smoking in US adolescents. *Addiction.* 1998;93(3):433–440.

6. Tyas SL, Pederson LL. Psychosocial factors related to adolescent smoking: a critical review of the literature. *Tob Control.* 1998;7(4):409–420.

7. Weinberg NZ, Rahdert E, Colliver JD, Glantz MD. Adolescent substance abuse: a review of the past 10 years. *J Am Acad Child Adolesc Psychiatry.* 1998;37 (3):252–261.

8. Lewinsohn PM, Rohde P, Seeley JR, Klein DN, Gotlib IH. Natural course of adolescent major depressive disorder in a community sample: predictors of recurrence in young adults. *Am J Psychiatry.* 2000;157(10):1584–1591.

9. Rao U, Ryan ND, Birmaher B, et al. Unipolar depression in adolescents: clinical outcome in adulthood. *J Am Acad Child Adolesc Psychiatry.* 1995;34(5):566–578.

10. Mair CF, Diez Roux AV, Galea S. Are neighborhood characteristics associated with depressive symptoms? A critical review. *J Epidemiol Community Health.* 2008;62 (11):940–946.

11. Truong KD, Ma S. A systematic review of relations between neighborhoods and mental health. *J Ment Health Policy Econ.* 2006;9(3):134–154.

12. Xue Y, Leventhal T, Brooks-Gunn J, Earls FJ. Neighborhood residence and mental health problems of 5- to 11-year olds. *Arch Gen Psychiatry.* 2005;62 (5):554–563.

13. Leventhal T, Brooks-Gunn J. Moving to opportunity: an experimental study of neighborhood effects on mental health. *Am J Public Health.* 2003;93(9):1576–1582.

14. Kim D. Blues from the neighborhood? Neighborhood characteristics and depression. *Epidemiol Rev.* 2008;30(1):101–117.

15. Virtanen M, Ervasti J, Oksanen T, Kivimaki M, Vahtera J. Social capital in schools. In: Kawachi I, Takao S, Subramanian SV, eds. *Global Perspectives on Social Capital and Health.* New York, NY: Springer; 2013: 65–85.

16. Kidger J, Araya R, Donovan J, Gunnell D. The effect of the school environment on the emotional health of adolescents: a systematic review. *Pediatrics.* 2012;129 (5):925–949.

17. Kuperminc GP, Leadbeater BJ, Blatt SJ. School social climate and individual differences in vulnerability to psychopathology among middle school students. *J Sch Psychol.* 2001;39(2):141–159.

18. Resnick MD, Bearman PS, Blum RW, et al. Protecting adolescents from harm: findings from the National Longitudinal Study on Adolescent Health. *JAMA.* 1997;278(10):823–832.

19. Jacobson KC, Rowe DC. Genetic and environmental influences on the relationship between family connectedness, school connectedness and adolescent depressed mood: sex differences. *Dev Psychol.* 1999;35(4):926–939.

20. Kasen S, Johnson J, Cohen P. The impact of school emotional climate on student psychopathology. *J Abnorm Child Psychol.* 1990;18(2):165–177.

21. Bond L, Butler H, Thomas L, Carlin J, Glover S, Bowes G, et al. Social and school connectedness in early secondary schools as predictors of late teenage substance use, mental health, and academic outcomes. *J Adolesc Health.* 2007;40:357.e9–357.e18.

22. Way N, Reddy R, Rhodes J. Students' perceptions of school climate during the middle school years: associations with trajectories of psychological and behavioral adjustment. *Am J Community Psychol.* 2007;40(3–4): 194–213.

23. Anderman EM. School effects on psychological outcomes during adolescence. *J Educ Psychol.* 2002;94 (4):795–809.

24. Goodman E, Huang B, Wade TJ, Kahn RS. A multilevel analysis of the relation of socioeconomic status to adolescent depressive symptoms: does school context matter? *J Pediatr.* 2003;143(4):451–456.

25. Briere FN, Pascal S, Dupere V, Janosz M. School environment and adolescent depressive symptoms: a multilevel longitudinal study. *Pediatrics.* 2013;131: e702–e708.

26. Catalano RF, Haggerty KP, Oesterle S, Fleming CB, Hawkins JD. The importance of bonding to school for healthy development: findings from the Social Development Research Group. *J Sch Health.* 2004;74(7):252–261.

27. Sellstrom E, Bremberg S. Is there a "school effect" on pupil outcomes? A review of multilevel studies. *J Epidemiol Community Health.* 2006;60(2):149–155.

28. Reis J, Trockel M, Mulhall P. Individual and school predictors of middle school aggression. *Youth Soc.* 2007;38(3):322–347.

29. Green JG, Dunn EC, Johnson RM, Molnar BE. A multi-level investigation of the association between school context and adolescent non-physical bully victimization. *J Sch Violence.* 2011;10(2):133–149.

30. Roeser RW, Eccles JS, Sameroff AJ. School as a context of early adolescent academic and social-emotional development: a summary of research findings. *Elem Sch J.* 2000;100(5):443–471.

31. Hoge DR, Smit EK, Hanson SL. School experiences predicting changes in self-esteem of sixth- and seventh-grade students. *J Educ Psychol.* 1990;82(1):117–127.

32. Dunn EC, Grief Green J, Johnson RM. The Modified Depression Scale (MDS): a brief, no-cost assessment tool to estimate the level of depressive symptoms in students and schools. *School Ment Health.* 2012;4(1):34–45.

33. Leventhal T, Brooks-Gunn J. The neighborhoods they live in: the effects of neighborhood residence on child and adolescent outcomes. *Psychol Bull.* 2000;126 (2):309–337.

34. Beretvas SN. Cross-classified and multiple-membership models. In: Hox JJ, Roberts JK, eds. *Handbook of Advanced Multilevel Analysis.* New York, NY: Routledge; 2011:313–334.

35. Goldstein H. Multilevel cross-classified models. *Sociol Methods Res.* 1994;22(3):364–375.

36. Aud S, Hussar W, Planty M, et al. *The Condition of Education 2010.* Washington, DC: National Center for Education Statistics, Institute of Education Sciences, US Department of Education; 2010.

37. Roeser RW, Eccles JS, eds. *Schooling and Mental Health.* New York, NY: Kluwer Academic/Plenum Publishers; 2000.

38. Gershoff ET, Aber JL, eds. *Neighborhoods and Schools: Contexts and Consequences for the Mental Health and Risk Behaviors of Children and Youth.* New York, NY: Psychology Press; 2006.

39. Carroll-Scott A, Gilstad-Hayden K, Rosenthal L, et al. Disentangling neighborhood contextual associations with child body mass index, diet, and physical activity: the role of built, socioeconomic, and social environments. *Soc Sci Med.* 2013;95:106–114.

40. Macintyre S, Ellaway A, eds. *Ecological Approaches: Rediscovering the Role of the Physical and Social Environment.* New York, NY: Oxford University Press; 2000.

41. Tendulkar SA, Buka S, Dunn EC, Subramanian SV, Koenen KC. A multilevel investigation of neighborhood effects on parental warmth. *J Community Psychol.* 2010;38(5):557–573.

42. Sampson RJ, Raudenbush S, Earls F. Neighborhoods and violent crime: a multilevel study of collective efficacy. *Science.* 1997;277(5328):918–924.

43. Grady S, Bielick S. Trends in the use of school choice: 1993 to 2007. Available at: http://nces.ed.gov/pubs2010/2010004.pdf. Accessed December 1, 2014.

44. Snyder TD, Dillow SA. *Digest of Education Statistics, 2012.* Washington, DC: National Center for Education Statistics, Institute of Education Sciences, US Department of Education; 2013.

45. Harris KM. *The Add Health Study: Design and Accomplishments.* Chapel Hill, NC: Carolina Population Center, University of North Carolina; 2013.

46. Radloff LS. The CES-D scale: a self-report depression scale for research in the general population. *Appl Psychol Meas.* 1977;1(3):385–401.

47. Tabachnick BG, Fidell LS. *Using Multivariate Statistics.* 6th ed. Boston, MA: Allyn & Bacon; 2013.

48. van Belle G. *STRUTS: Statistical Rules of Thumb.* New York, NY: John Wiley & Sons Inc; 2002.

49. Browne NJ. *MCMC Estimation in MLwiN Version 2.0.* London, England: Centre for Multilevel Modeling, Institute of Education; 2004.

50. Raudenbush SW, Bryk AS. *Hierarchical Linear Models: Applications and Data Analysis Methods.* 2nd ed. Thousand Oaks, CA: Sage Publications; 2002.

51. Lee ES, Forthofer RN. *Analyzing Complex Survey Data.* Thousand Oaks, CA: Sage Publications; 2006.

52. Dunn EC, Richmond TK, Milliren CE, Subramanian SV. Using cross-classified multilevel models to disentangle school and neighborhood effects: an example focusing on smoking behaviors among adolescents in the United States. *Health & Place.* 2015;31:224–232.

53. Wight RG, Aneshensel CS, Botticello AL, Sepulveda JE. A multilevel analysis of ethnic variation in depressive symptoms among adolescents in the United States. *Soc Sci Med.* 2005;60(9):2073–2084.

54. Wickrama KAS, Bryant CM. Community context of social resources and adolescent mental health. *J Marriage Fam.* 2003;65(4):850–866.

55. Hull P, Kilbourne B, Reece M, Husaini B. Community involvement and adolescent mental health: moderating effects of race/ethnicity and neighborhood disadvantage. *J Community Psychol.* 2008;36(4):534–551.

56. Wight RG, Botticello AL, Aneshensel CS. Socioeconomic context, social support, and adolescent mental health: a multilevel investigation. *J Youth Adolesc.* 2006;35(1):109–120.

57.   Aminzadeh K, Denny S, Utter J, et al. Neighbour-hood social capital and adolescent self-reported wellbeing in New Zealand: a multilevel analysis. *Soc Sci Med.* 2013;84:13–21.

58.   Mellanby AR, Rees JB, Tripp JH. Peer-led and adult-led school health education: a critical review of available comparative research. *Health Educ Res.* 2000;15(5):533–545.

59.   Rones M, Hoagwood K. School-based mental health services: a research review. *Clin Child Fam Psychol Rev.* 2000;3(4):223–241.

60.   Greenberg MT, Weissberg RP, O'Brien MU, et al. Enhancing school-based prevention and youth develop-ment through coordinated social, emotional, and aca-demic learning. *Am Psychol.* 2003;58(6–7):466–474.

61.   Eccles JS, Roeser RW. School and community influences on human development. In: Bornstein MH, Lamb ME, eds. *Developmental Science: An Advanced Textbook.* 6th ed. New York, NY: Psychology Press; 2011:571–643.

62.   Jones SM, Brown JL, Aber JL. Two-year impacts of a universal school-based social-emotional and literacy intervention: an experiment in translational develop-mental research. *Child Dev.* 2011;82(2):533–554.

63.   Horowitz JL, Garber J. The prevention of depressive symptoms in children and adolescents: a meta-analytic review. *J Consult Clin Psychol.* 2006;74(3):401–415.

64.   Weist MD, Evans SW, Lever NA, eds. *Handbook of School Mental Health: Advancing Practice and Research.* New York, NY: Kluwer Academic/Plenum Publishers; 2003.

65.   Ringeisen H, Henderson K, Hoagwood K. Context matters: schools and the "research to practice gap" in children's mental health. *School Psych Rev.* 2003;32 (2):153–168.

66.   Dunn EC, Masyn KE, Yudron M, Jones SM, Subramanian SV. Translating multilevel theory into multilevel research: challenge and opportunities for un-derstanding the social determinants of psychiatric disor-ders. *Soc Psychiatry Psychiatr Epidemiol.* 2014;49 (6):859–872.

67.   Vallee J, Cadot E, Roustit C, Parizot I, Chauvin P. The role of daily mobility in mental health inequalities: the interactive influence of activity space and neigh-bourhood of residence on depression. *Soc Sci Med.* 2011;73(8):1133–1144.