Multiple contexts and adolescent body mass index: Schools, neighborhoods, and social networks

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ABSTRACT

Adolescent health and behaviors are influenced by multiple contexts, including schools, neighborhoods, and social networks, yet these contexts are rarely considered simultaneously. In this study we combine social network community detection analysis and cross-classified multilevel modeling in order to compare the contributions of each of these three contexts to the total variation in adolescent body mass index (BMI). Wave 1 of the National Longitudinal Study of Adolescent to Adult Health is used, and for robustness we conduct the analysis in both the core sample (122 schools; $N = 14,144$) and a sub-set of the sample (16 schools; $N = 3335$), known as the saturated sample due to its completeness of neighborhood data. After adjusting for relevant covariates, we find that the school-level and neighborhood-level contributions to the variance are modest compared with the network community-level ($\sigma^2_{school} = 0.069$, $\sigma^2_{neighborhood} = 0.144$, $\sigma^2_{network} = 0.463$). These results are robust to two alternative algorithms for specifying network communities, and to analysis in the saturated sample. While this study does not determine whether network effects are attributable to social influence or selection, it does highlight the salience of adolescent social networks and indicates that they may be a promising context to address in the design of health promotion programs.

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1. Introduction

Multiple contexts are relevant in shaping individual and population-level health and health behaviors. These include both *physically or spatially defined environments*, such as neighborhoods, schools, and workplaces, and *socially defined environments*, such as the social networks within which individuals are embedded. Historically these contexts have often been studied individually, likely due to the recentness of the availability of methods capable of addressing them simultaneously (Dunn et al., 2015b; Rasbash and Goldstein, 1994), such as cross-classified multilevel modeling (CCMM). Since the development of CCMM, researchers have used them most frequently to study the *simultaneous* and *relative* contributions of schools and neighborhoods (Aminzadeh et al., 2013; Dunn et al., 2015a, 2015b; Teitler and Weiss, 2000; West et al., 2004), and workplaces and neighborhoods (Moore et al., 2013; Muntaner et al., 2006, 2011; Virtanen et al., 2010) to variation in

health behaviors and outcomes. However, studies have rarely bridged the domains of social networks and physical environments, and never within a CCMM framework. This gap in current knowledge is critical to address for two major reasons. First, there is tremendous value in ascertaining the *relative* contributions made by these contexts to the distribution of particular health behaviors and outcomes, as this would enable researchers and policy makers to more effectively target interventions and policies to address heath inequalities (Merlo et al., 2012). Second, omitting potentially relevant contexts from analyses—particularly those using CCMM—may result in *omitted context bias*, or the attribution of variance associated with the omitted level to the included level or levels (Dunn et al., 2015b; Meyers and Beretvas, 2006).

In this study we apply a novel combination of social network community detection analysis and cross-classified multilevel modeling to address this knowledge gap by directly and explicitly comparing the contributions of each of three contexts—schools, neighborhoods, and social networks—to the total variation in adolescent body mass index (BMI). The analysis is conducted using data from wave 1 of the National Longitudinal Study of Adolescent to Adult Health, herein referred to by the official shortened title

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"Add Health". Adolescent body mass index (BMI) is the focus of this study for two main reasons. First, all three contexts have been implicated in prior research as highly relevant to shaping individual-level and population-level distributions of adolescent BMI. Second, the obesity epidemic among children and adolescents in the United States represents a major public health challenge due both to its scope (Ogden et al., 2012) and numerous comorbidities (Ferraro and Kelley-Moore, 2003; National Institute of Health, (1998)). Disentangling the contributions of relevant contexts that shape this epidemic will be key to addressing it.

1.1. Schools

The clustering of child and adolescent weight status by school-level has been found in a variety of data sets and populations (Procter et al., 2008; Richmond and Subramanian, 2008; Townsend et al., 2012). In particular, school-level factors that have been linked to student BMI, physical activity levels, and healthiness of diets, include: socioeconomic status (Miyazaki and Stack, 2015; Richmond et al., 2006; Richmond and Subramanian, 2008), the prevalence of school food practices (*e.g.*, using food as rewards and incentives) (Kubik et al., 2005), aspects of the school built environment such as rural locality, school size and setting, and playground area (Gomes et al., 2014; Miyazaki and Stack, 2015), and aspects of the school curriculum, such as frequency and duration of physical education classes, the qualification of physical education teachers, and the presence of school-based nutrition programs (Gomes et al., 2014; Veugelers and Fitzgerald, 2005). These findings have situated schools in the policy limelight as both potential shapers of child and adolescent diet and physical activity, and as potential locales for the implementation of health promotion programs.

1.2. Neighborhoods

Neighborhoods have similarly been identified as salient to the clustering of child and adolescent BMI (Townsend et al., 2012). Aspects of neighborhood *built environments*, such as proximity and access to parks, physical activity establishments, grocery stores, and fast food providers (Carroll-Scott et al., 2013; Schwartz et al., 2011), aspects of neighborhood *socioeconomic environments*, particularly area deprivation (Carroll-Scott et al., 2013; Grow et al., 2010; Schwartz et al., 2011; Townsend et al., 2012), and aspects of neighborhood *social environments*, including neighborhood crime, safety, and social connectivity (Carroll-Scott et al., 2013; Molnar et al., 2004), have been linked to child and adolescent BMI, healthy and unhealthy eating behaviors, physical activity levels, and hours of sedentary screen time.

1.3. Social networks

The structuring of social networks by health status has become an intriguing new area of research. Among both adolescents (Trogdon et al., 2008; Valente et al., 2009) and adults (Christakis and Fowler, 2007), a tendency for individuals with overweight or obesity to cluster, or in other words, for friends to be similar to each other in terms of weight status, has been found. A recent review (Fletcher et al., 2011) of social network analyses evaluating the eating behaviors and bodyweight of young people found consistent evidence that school friends are clustered according to BMI, and that the frequency of fast food consumption clusters within groups of boys, whereas body image concerns, dieting, and eating disorders cluster among girls. Additionally, youth affected by overweight are less likely to be popular and more likely to be socially isolated.

It is not the purpose of this study to disentangle the roles of *selection* (the tendency for individuals to preferentially select friends who are similar to them in weight status, or other characteristics that are correlated with weight status) and *social influence* (the social contagion of behaviors with relevance to weight status, such as diet and exercise) in generating clustering of weight status in social networks. Instead we address another primary concern (Cohen-Cole and Fletcher 2008; Fowler and Christakis 2008)—the disentangling of the roles of shared environments such as schools and neighborhoods from network effects.

1.4. Simultaneous contexts

The substantive goal of this study is to determine the *relative* contributions of schools, neighborhoods of residence, and adolescent school-based peer networks to the variance of BMI observed. Studies addressing the simultaneous roles of schools and neighborhoods have consistently determined that both contexts contribute significantly to the variance in adolescent BMI and physical activity (Townsend et al., 2012), yet such studies are still rare, and none that we are aware of have included adolescent peer networks as well.

Studies that have addressed the roles of both social networks (broadly defined) and environments to health outcomes of any kind are uncommon. In a recent review we conducted, these studies fell into three categories. In Category 1, network analyses involved the use of friend (or "alter") attributes to predict attributes of individuals (or "egos") of interest, while school environments were controlled for as fixed effects (Ali et al., 2011a,b; Ali and Dwyer, 2011; Ali et al., 2011c; Ali and Dwyer, 2010; Cohen-Cole and Fletcher, 2008; Cohen-Cole and Fletcher, 2009; Trogdon et al., 2008). Variants on this theme include studies where the effect of alters on egos was evaluated based on geographic distance to determine whether the effect degraded as distance increased (Christakis and Fowler, 2007; 2008). The hallmark of studies belonging to this category is that environment is treated as a confounder to be adjusted for, rather than as a separate contributor to the variance that is of substantive interest.

Studies in Category 2 included both network covariates (such as rate of cholera in a social community) and environment covariates (such as rate of cholera in a spatial community) as fixed effect predictors in regression models (Emch et al., 2012; Giebultowicz et al., 2011a, 2011b). Variants of studies in this category would include covariates for constructs related to social networks, such as social capital (Richmond et al., 2014), though we did not specifically review that literature. While studies such as these enable comparisons of particular aspects of networks or environments that may be of interest, this approach does not enable an evaluation of the holistic contributions made by networks and environments.

Category 3 included only one study, which was recently published by Perez-Heydrich et al. (2013). In this study, networks were represented using fixed effects and neighborhood elements were included as spatial autoregression coefficients in order to correct for spatial dependence. This innovative approach to understanding both social and spatial processes is worthy of further exploration. However, for our current purposes this approach does not enable a direct comparison of the relative influence of networks and environment contexts.

This review highlights two points. First, BMI and obesity were addressed in a networks context but only in Category 1, where environment was not usually of substantive interest. Second, an innovative approach is required in order to directly compare and better understand the simultaneity of multiple contexts. In this study we present a novel analytic approach, combining social network analysis and multilevel modeling, to disentangle and compare school, neighborhood, and social network contexts.

The goal of network community detection is to identify clusters of individuals in networks that are relatively densely connected to each other and sparsely connected to others outside their group. Ideally, network community detection in *social* networks identifies groups that socialize regularly and potentially have their own social norms. These groups may bring together individuals who, while not necessarily nominating each other as friends, are at least closely woven together in their surrounding social fabric. Individuals within the same network community therefore may exert influence on each other through social processes and generally contribute to the shared social environment. This treatment of network expands our conceptualization of the relevant social context beyond the immediate social connections of each individual to consider the larger social environment, which includes relatively short indirect connections.

By utilizing a CCMM framework and focusing on contributions to variance, we situate this paper within multilevel eco-epidemiologic approaches that seek to understand the determinants of individual heterogeneity, rather than identify probabilistic risk factors (Merlo, 2014).

2. Methods

2.1. Data

The National Longitudinal Study of Adolescent to Adult Health (Add Health) is a longitudinal study of a nationally representative sample of US adolescents who were in grades 7–12 in the first wave of interviews (1994–1995) (Harris et al., 2009). The primary sampling frame was derived from the Quality Education Database and was used to select a stratified sample of 80 high schools with probability proportional to size, as well as 52 middle schools that were paired to the high schools as feeders. Schools were stratified based on region, urbanicity, school type (public, private, parochial), ethnic mix and size. A unique aspect of the Add Health data is that students were asked to nominate up to 10 of their closest friends (5 male and 5 female), and therefore it is possible to construct sociocentric social network for each school. In wave 1, social network questions were administered in both the in-school questionnaire and in an in-home questionnaire, which was administered to a sub-sample of students from each school (referred to as the "core sample") (Fig. 1). The core sample was selected through a combination of stratified random sampling (to ensure a mix of students across grades and ages) and oversampling of racial and ethnic minorities. The in-home questionnaire also captured greater detail of student health and identifiers of neighborhood of residence.

In two large high schools and fourteen smaller middle schools and high schools, in-home interviews were attempted with *all* students in wave 1. These 16 schools represent a "saturated sample" for which neighborhood identifiers and BMI data are available for most students.

Add Health is an ideal data set in which to study the joint contributions of networks and environment, since few other data sets contain both excellent social network data and environment data.

2.2. Sample

In this study, primary analyses are conducted in the core sample ($N = 20,745$) among adolescents for whom we have matching in-school questionnaires. Initially the entire in-school sample's social network data ($N = 90,118$) was used to construct relatively complete social networks for each school or pair of middle schools and high schools (Fig. 1). These networks were used in the network community detection analyses to identify the social network

communities, or social groups, to which individual students belonged. The in-school survey was very limited in scope and therefore using the in-school sample for the entire analysis is not possible. However, beginning with the in-school sample enables us to determine network community membership with improved validity, and the core sample that was selected from the in-school sample through (predominantly) random processes provides us with a sufficient representation of the entire school population. Some schools were dropped from the sample due to insufficient sample size after the in-school and in-home matching processes and reductions based on missing the BMI outcome, leaving a sample of 122 schools and $N = 14,144$ students (68% of the original core sample).

To test the robustness of our findings, analyses were also conducted in the "saturated sample" of 16 schools, for which we have nearly complete social network, BMI, and neighborhood data ($N = 3335$). The in-home questionnaire network data was used for the saturated sample. While not a random sample, the saturated sample schools are diverse. The two large schools were selected purposely by the Add Health researchers—one because it was a predominantly white rural public high school, and the other because it was racially and ethnically diverse (predominately Hispanic, black and Asian) and located in a major metropolitan area. The other 14 schools represent public (n = 9), private (n = 4), and Catholic (n = 1) schools in the West (n = 3), South (n = 4), Northeast (n = 3), and Midwest (n = 4) regions.

2.3. Outcome: body mass index

Body mass index (BMI) was constructed using self-reported height and weight. Goodman et al., (2000) confirmed the validity of these measures in Add Health using wave 2 data and comparing the self-reported with actual measures of height and weight. We treat BMI as it was originally intended, which is as a population-level indicator of social experience.

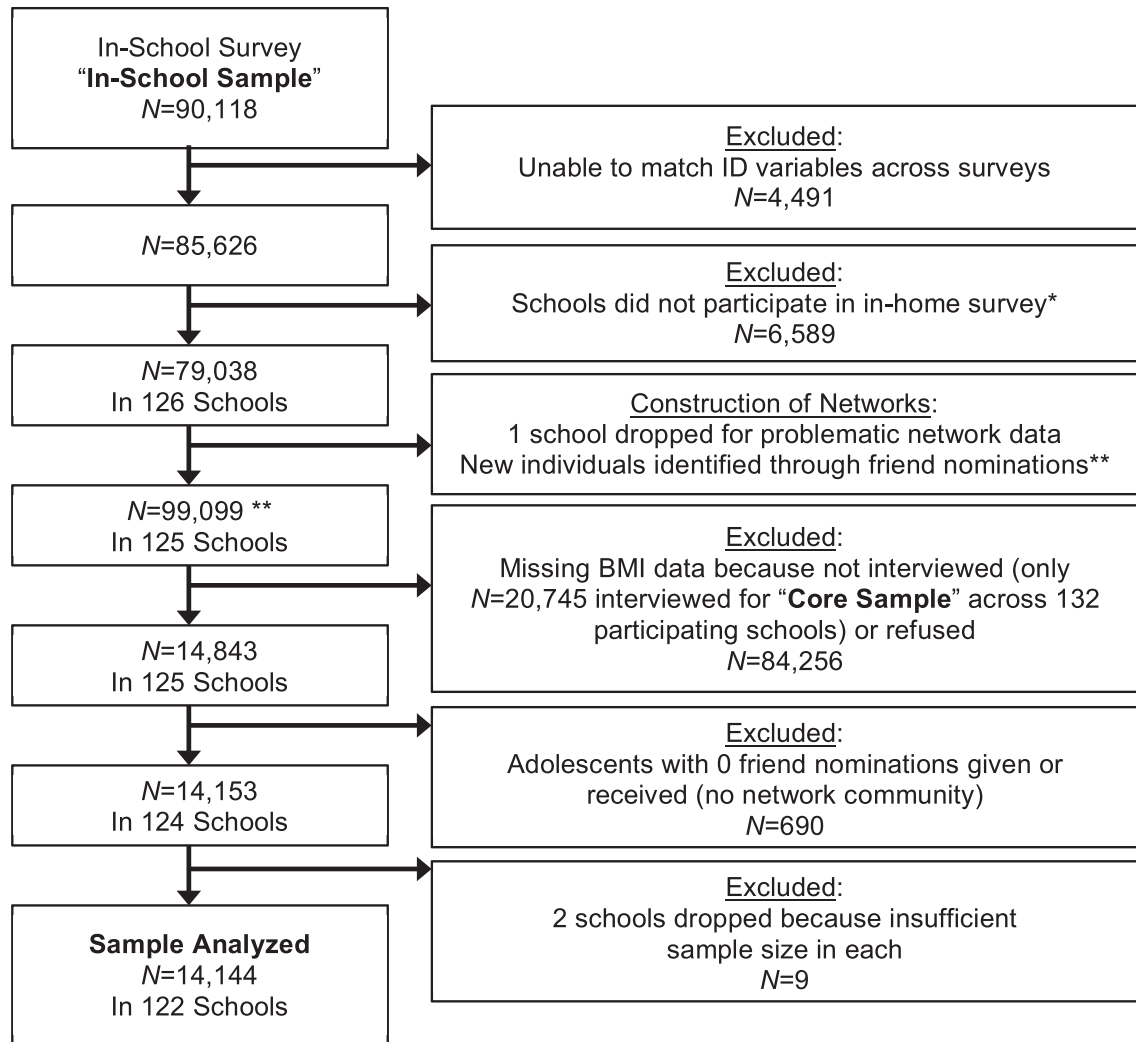### 2.4. Exposures

2.4.1. Neighborhoods and schools
Unique IDs for each school and neighborhood of residence (census tract) are available in the Add Health sample, enabling a clear nesting of individual students within the schools they attend and neighborhoods they reside in.

2.4.2. Social networks
Respondent nominations of friends were used to construct social networks. The nomination items took the following form: *"List your closest* [male/female] *friends. List your best* [male/female] *friend first, then your next best friend, and so on."* Students were provided with a roster of students attending their school and paired sister-school, enabling them to nominate friends using ID codes specific to each individual. All friend nominations are assumed to be reciprocated relationships (i.e., the networks are undirected) because this expands the variation in the numbers of connections observed (i.e., some individuals may have more than 5 male or 5 female friends but were unable to nominate them all due to the limitations imposed by the survey). Friends who were nominated but not surveyed, due to refusal or absence from school when the survey was administered, are included in network structures for network community detection purposes but are excluded from the final analysis for missing BMI.

2.4.3. Covariates
Standard demographic covariates in BMI models, including sex, race/ethnicity, parent education, and age, are adjusted for in order

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┌─────────────────────────┐
│     In-School Survey    │
│   "In-School Sample"    │         ┌──────────────────────────────────────────┐
│       N=90,118          │────────▶│                 Excluded:                  │
└─────────────────────────┘         │   Unable to match ID variables across surveys │
             │                       │                  N=4,491                   │
             ▼                       └──────────────────────────────────────────┘
┌─────────────────────────┐         ┌──────────────────────────────────────────┐
│       N=85,626          │────────▶│                 Excluded:                  │
└─────────────────────────┘         │  Schools did not participate in in-home survey* │
             │                       │                  N=6,589                   │
             ▼                       └──────────────────────────────────────────┘
┌─────────────────────────┐         ┌──────────────────────────────────────────┐
│       N=79,038          │         │          Construction of Networks:          │
│     In 126 Schools      │────────▶│  1 school dropped for problematic network data │
└─────────────────────────┘         │ New individuals identified through friend nominations** │
             │                       └──────────────────────────────────────────┘
             ▼                       ┌──────────────────────────────────────────┐
┌─────────────────────────┐         │                 Excluded:                  │
│      N=99,099 **        │         │   Missing BMI data because not interviewed (only │
│     In 125 Schools      │────────▶│  N=20,745 interviewed for "Core Sample" across 132 │
└─────────────────────────┘         │          participating schools) or refused         │
             │                       │                  N=84,256                  │
             ▼                       └──────────────────────────────────────────┘
┌─────────────────────────┐         ┌──────────────────────────────────────────┐
│       N=14,843          │         │                 Excluded:                  │
│     In 125 Schools      │────────▶│  Adolescents with 0 friend nominations given or │
└─────────────────────────┘         │        received (no network community)        │
             │                       │                   N=690                    │
             ▼                       └──────────────────────────────────────────┘
┌─────────────────────────┐         ┌──────────────────────────────────────────┐
│       N=14,153          │         │                 Excluded:                  │
│     In 124 Schools      │────────▶│      2 schools dropped because insufficient      │
└─────────────────────────┘         │           sample size in each             │
             │                       │                    N=9                     │
             ▼                       └──────────────────────────────────────────┘
┌─────────────────────────┐
│    Sample Analyzed      │
│       N=14,144          │
│     In 122 Schools      │
└─────────────────────────┘
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Notes:

In-School Sample: from in-school survey (N=90,118); very limited questionnaire but contains more complete network structure data for each school.

Core Sample: a subset of students from 132 schools were contacted for a more in-depth in-home survey (N=20,745). Neighborhood and BMI data come from this questionnaire.

Saturated Sample: of the 132 schools participating in the in-home survey, 16 were selected to have in-home surveys attempted will all students in the school, rather than only a random sample.

* A total of 172 schools are listed in the in-school questionnaire, however only 132 schools participated in the in-home survey.

** Non-respondents were identified when their friends nominated them in the network data. These adolescents were temporarily added to the data set in order to account for them in the network structure when applying network community detection algorithms. They were later dropped for missing BMI data.

Fig. 1. Data management and exclusions.

to distinguish between composition and context-level variation. Models in the core sample also adjusted for US region (West, Midwest, South, and Northeast).

Sex and race/ethnicity were self-reported by respondents (sometimes interviewers confirmed responses to these items with respondents). Sex was available only as a dichotomous variable; the survey was not constructed to measure gender, which we would generally prefer to use. Race/ethnicity categories include: (1) Hispanic or Latino all races, (2) black or African American, (3) Asian, (4)

Native American, (5) white, and (6) other. We hasten to note that we conceptualize race here as a proxy for racialized experiences (e.g., discrimination) and not as a factor with any biological significance. Age was calculated based on the interview date and the self-reported birthday of the respondent.

Parent education was defined as the highest completed level of education attained by either parent or parent-figure in the respondent's household. Since parent education information was requested multiple times in the wave 1 interviews, the order of

preference for determination of education levels was: (1) provided by the parent or parent's spouse/partner in the parent in-home questionnaire, (2) provided by the student in the in-home questionnaire, (3) provided by the student in the in-school questionnaire.

3. Analysis

3.1. Network community detection

While network communities are conceptually intuitive, identifying communities in practice requires application of strict definitions for what counts as a sufficiently dense cluster to warrant labeling a set of individuals as members of the same network community.

Modularity maximization network community detection algorithms have become widely used because they partition a variety of network graphs into apparently meaningful network communities (Porter et al., 2009)The modularity maximization algorithm used in this analysis was developed by Blondel et al. (2008). There are many different ways a given network can be partitioned, and modularity refers to the quality of a particular set of network partitions. Quality of a set of network partitions in this case is evaluated based on the number of ties that run between nodes (e.g., adolescents) in the same network communities relative to the number of such ties we would expect if ties were created between nodes at random (while holding constant the number of ties of each node) (Newman, 2006). Modularity maximization algorithms use a variety of heuristics to optimize the modularity score and partition networks into network communities.

Since different detection algorithms may yield different network community membership lists and different total numbers of network communities for the same network, we evaluated the robustness of our findings to network community specification by applying a second algorithm—*k-clique percolation*—which is becoming particularly popular in analyses of *social* networks (Fortunato, 2010). K-clique percolation is a deterministic algorithm that begins with specifying the minimum size of a clique (k), or group where all members are friends with every other member (Palla et al., 2005). For instance, a clique of size $k = 3$ is a group of three adolescents, all of whom are friends with each other. Previous research using k-clique percolation in the Add Health data set found that cliques of size $k = 3$ were optimal (González et al., 2007). In k-clique percolation, all cliques within a network are identified, and then any cliques that share at least $k-1$ members will be defined as members of the same network community.

Within this definition, individuals are allowed to simultaneously belong to two or more network communities, whereas in modularity maximization individuals are nested within only one network community. In this analysis, in order to nest individuals within a single network community, if an adolescent belongs to multiple network communities he or she will be included as a member of the community to which they have the most friendship links. In the event of a tie, they are randomly assigned to one of the network communities to which they have the most friendship links. Additionally, some socially marginalized individuals who are not members of cliques are unable to be associated with particular network communities, and therefore are excluded in this analysis from models addressing networks.

3.2. Cross-classified data

In the core sample, students from the same neighborhood may attend different schools, and students in the same school reside in different neighborhoods. Furthermore, because friend nominations can link individuals across paired schools, there is no clear hierarchical nesting of social network communities within schools. Students within a single network community can also reside in multiple neighborhoods, and students from the same neighborhood can participate in different network communities. In the core sample, therefore, the three contexts—schools, neighborhoods, and social network communities—are cross-classified, with no clear hierarchy (Fig. 2A).

In the saturated sample, none of the schools are paired and therefore there is a clear hierarchy—network communities are nested within schools and neighborhoods are nested within schools. However, because students from the same neighborhood can still participate in different network communities, and network communities are composed of students from multiple neighborhoods, the network community and neighborhood levels are still cross-classified (Fig. 2B).

3.3. Models

A series of eight models are fit in both the core sample and saturated sample in order to iterate through all combinations of contexts. In the core sample, Model 1 is a single-level linear model of BMI where adolescents are not nested within any context. Models 2, 3 and 4 are two-level hierarchical models—Model 2 nests adolescents in neighborhoods, Model 3 nests adolescents in schools, and Model 4 nests adolescents in their social network communities. Models 5, 6, and 7 iterate through paired combinations of contexts using cross-classified multilevel models (CCMM). Model 5 nests adolescents simultaneously in both network communities and neighborhoods, Model 6 nests adolescents in neighborhoods and schools, and Model 7 nests adolescents in network communities and schools. The final model, Model 8, is a CCMM that nests adolescents in schools, neighborhoods, and network communities. Because of the partially hierarchical structure in the saturated sample, a combination of CCMM and three-level hierarchical models are used as appropriate.

In the core sample, each model was fit four times: as a null model, a model adjusted for US region, a model adjusted for demographic covariates, and as a model adjusted for both demographic covariates and US region. In the saturated sample, school dummy variables were included when appropriate (in models not also treating school as a level).

4. Results

Network community detection was performed in Python 2.7 (Anaconda by Continuum Analytics, 2015). The k-clique percolation algorithm *k_clique_communities* from the NetworkX (Hagberg et al., 2008) library and modularity maximization algorithm *community_multilevel* from the IGraph library (Csardi and Nepusz, 2006) were used in network community detection. All multilevel analyses were conducted in MLwiN version 2.32 (Rasbash et al., 2015) using Bayesian Markov Chain Monte Carlo (MCMC) estimation procedures (Browne, 2009). The regression models were first fit using Iterative Generalized Least Squares (IGLS) estimation to provide the Bayesian MCMC procedure with initialization values; Non-informative priors and burn-in of 500 iterations were used in all analyses. MCMC estimation was run in all models for a minimum of 150,000 iterations, though most models achieved convergence significantly before that point.

Descriptive statistics for the sample are provided in Table 1. The core sample ($N = 14,144$) was predominantly white, black and Hispanic, with a mean age of 15.6 and mean BMI of 22.5 kg/m^2. Further information about the multilevel structure of the data is provided in Table 2. In the core sample, adolescents are distributed
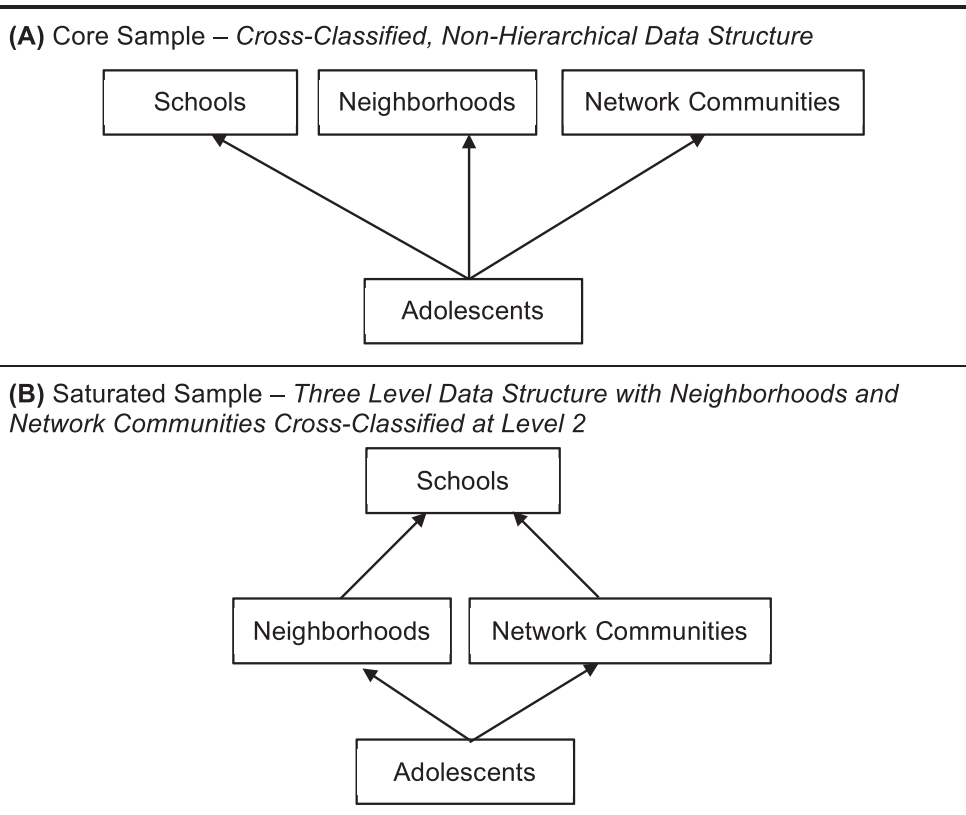
(A) Core Sample – *Cross-Classified, Non-Hierarchical Data Structure*

(B) Saturated Sample – *Three Level Data Structure with Neighborhoods and Network Communities Cross-Classified at Level 2*

Fig. 2. Schematics illustrating data structures in core and saturated samples.

Table 1
Sample demographics.

	Core sample		Saturated sample	
	N	(%)	N	(%)
Total	14144	(100.00%)	3335	(100.00%)
Sex				
Female	7262	(51.34%)	1630	(48.88%)
Male	6882	(48.66%)	1705	(51.12%)
Race/ethnicity				
Hispanic	2233	(15.79%)	668	(20.03%)
White	7244	(51.22%)	1596	(47.86%)
Black	3191	(22.56%)	477	(14.30%)
Asian	1071	(7.57%)	520	(15.59%)
Native American	248	(1.75%)	49	(1.47%)
Other	153	(1.08%)	23	(0.69%)
Missing	4	(0.03%)	2	(0.06%)
Parent education				
Less than high school	1506	(10.65%)	413	(12.38%)
Completed high school	3592	(25.40%)	883	(26.48%)
Some college	4034	(28.52%)	955	(28.64%)
Completed college or more	4924	(34.81%)	1056	(31.66%)
Missing	88	(0.62%)	28	(0.84%)

	N	N missing	Mean	(SD)	Min	Max
Core sample						
Age in wave 1 (years)	14141	3	15.61	(1.70)	11	21
BMI in wave 1 (kg/m^2)	14144	0	22.54	(4.43)	11.22	63.56
Saturated sample						
Age in wave 1 (years)	3335	0	16.09	(1.58)	12	20
BMI in wave 1 (kg/m^2)	3335	0	22.93	(4.51)	11.76	46.24

across 1931 neighborhoods, 122 schools, 930 modularity maximization network communities, and 2733 k-clique network communities (where clique size was $k = 3$). Due to "marginalized"

adolescents not being assigned network communities using the k-clique approach, in these models the sample was reduced to $N = 11,474$. Consistent with prior studies, a two-sided t-test revealed that marginalized adolescents had higher mean BMI (23.0 kg/m^2) than non-marginalized adolescents (22.4 kg/m^2). More detailed descriptions of the 16 school saturated sample are available in the online Supplemental Table 1.

Fig. 3 illustrates examples from the data of how social networks are partitioned subtly differently depending on the algorithm used. In general, the Blondel et al. (2008) modularity maximization algorithm partitioned the network graphs into network communities of more equal size, while k-clique percolation tended to split networks into a small number of large network communities and a large number of small communities.

Tables 3 and 4 provide results for all models fit in the core sample using modularity maximization network community detection. Results for models fit using k-clique detection are available in Supplemental Tables 2 and 3, while results for models fit in the saturated sample (using modularity maximization) are available in Supplemental Tables 4 and 5.

In the core sample and using modularity maximization, results from the two-level models (Models 2–4) find that all three contexts, when considered individually, contribute substantially to the total variance in BMI (Variance Partition Coefficients (VPC) in fully adjusted models: neighborhoods = 1.52%, schools = 1.09%, network communities = 2.96%). In Models 6, which cross-classifies neighborhoods and schools, both environmental contexts are attenuated slightly (VPCs: neighborhoods = 0.84%, schools = 0.71%), a result which is consistent with the literature and supports the claim that variance associated with omitted contexts will be attributed to contexts that are considered.

In the presence of cross-classification by network communities,

Table 2
Multilevel data structure of core and saturated samples.

	Core sample		Saturated sample	
	N	Mean number of students	N	Mean number of students
Students	14144	–	3335	–
Neighborhoods	1931	7.32	335	9.96
Schools	122	115.93	16	208.44
Network communities				
Modularity maximization	930	15.21	194	17.19
K-Clique percolation	2733	5.18	394	8.46
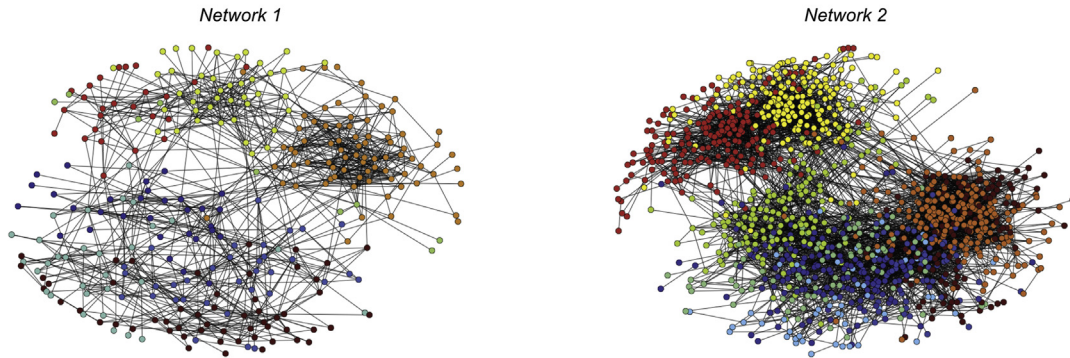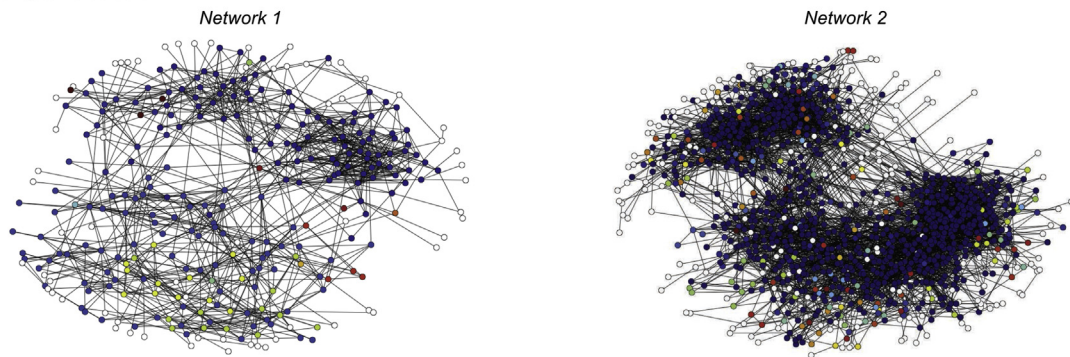
Note: Nodes of the same color within a single visualization of a network indicates membership in the same network community. In panel B, the k-clique percolation visuals, white nodes are not members of any network community (i.e., they are marginalized).

Fig. 3. Visualizations of detected communities in social networks using two algorithms — Modularity Maximization and K-clique Percolation.

both neighborhoods (Model 5: VPC = 1%) and schools (Model 7: VPC = 0.73%) are similarly attenuated. Surprisingly, the network effect detected in the two-level model largely remains after cross-classification by the other contexts (VPC for network communities: Model 5 = 2.64%, Model 7 = 2.48%). These results indicate both that network communities contribute substantially to the variance—more so than either neighborhoods or schools—and that their inclusion in models attenuates the variance attributable to neighborhoods and schools.

Surprisingly, in the final model (Model 8) where adolescents are nested in all three contexts simultaneously, the school-level contribution to the variance is significantly reduced (VPC = 0.37%). The neighborhood-level contribution to the variance is still modest though more robust than schools to the addition of network communities to the model (VPC = 0.77%). The network community-level contributes to the variance (VPC = 2.49%) more than twice what neighborhoods and schools contribute combined. According to the Deviance Information Criterion (DIC), smaller values of which indicate better model fit, Model 8 (DIC = 79818.38)

is modestly outperformed by Model 5 (DIC = 79808.04), indicating that the school-level does not substantially improve the model fit above and beyond what is achieved by cross-classifying neighborhoods and network communities.

These results are robust both to the specification of network communities using an alternative algorithm—k-clique percolation—and when the models are fit in the saturated sample. Interestingly, the magnitude of the network community-level contribution to the variance does depend on the detection method employed, however it is found to be substantial in both cases. In the fully adjusted Model 8, using k-clique network communities, the school-level and neighborhood-level contributions to the variance remain comparable to each other and modest relative to the network-level (VPCs: schools = 0.58%, neighborhoods = 0.53%, network = 11.19%). In the saturated sample, the model is optimized when all three contexts are accounted for, though network communities clearly emerge as contributing more to the total variance.

Table 3
Core sample – random effects results from single-level and two-level multilevel models, modularity maximization detection.

	Null model	Adjusted model – region[a]	Adjusted model – demographics [b]	Adjusted model – demographics & region[a,b]
	Estimate (VPC) [95% credible interval]	Estimate (VPC) [95% credible interval]	Estimate (VPC) [95% credible interval]	Estimate (VPC) [95% credible interval]
Model 1: *Single level model*				
Individual	19.655 [19.203, 20.117]	19.616 [19.165, 20.078]	18.625 [18.197, 19.066]	18.623 [18.192, 19.063]
DIC	82263.75	82235.32	80954.95	80952.77
Model 2: *Two level model – students nested in neighborhoods*				
Neighborhood	0.603 (3.06%) [0.426, 0.806]	0.586 (2.98%) [0.414, 0.787]	0.277 (1.49%) [0.154, 0.421]	0.284 (1.52%) [0.162, 0.430]
Individual	19.076 [18.624, 19.538]	19.056 [18.605, 19.518]	18.354 [17.919, 18.799]	18.343 [17.908, 18.786]
DIC	81238.32	81223.67	80155.93	80148.77
Model 3: *Two level model – students nested in schools*				
School	0.860 (4.35%) [0.616, 1.177]	0.817 (4.14%) [0.578, 1.127]	0.205 (1.10%) [0.110, 0.327]	0.204 (1.09%) [0.111, 0.326]
Individual	18.915 [18.478, 19.361]	18.915 [18.476, 19.363]	18.451 [18.022, 18.890]	18.448 [18.021, 18.884]
DIC	81720.14	81720.21	80822.88	80821.21
Model 4: *Two level model – students nested in network communities*				
Network	1.297 (**6.61%**) [1.059, 1.560]	1.255 (6.41%) [1.021, 1.515]	0.553 (2.98%) [0.408, 0.719]	0.551 (2.96%) [0.405, 0.718]
Individual	18.313 [17.879, 18.755]	18.318 [17.885, 18.761]	18.035 [17.609, 18.471]	18.035 [17.608, 18.470]
DIC	81264.07	81266.72	80501.38	80502.60

Notes: All models are fit using Markov Chain Monte Carlo (MCMC) estimation procedures.
DIC = Deviance Information Criterion. VPC = Variance Partition Coefficient.
[a] Demographic covariates: sex, race/ethnicity, parent education, and age.
[b] U.S. Regions: West, Midwest, South, and Northeast.

Table 4
Core sample – random effects results from three-level and cross-classified multilevel models, modularity maximization detection.

	Null model	Adjusted model – region[a]	Adjusted model – demographics[b]	Adjusted model – demographics & region[a,b]
	Estimate (VPC) [95% credible interval]	Estimate (VPC) [95% credible interval]	Estimate (VPC) [95% credible interval]	Estimate (VPC) [95% credible interval]
Model 5: *Cross-classified model – students nested in network communities and neighborhoods*				
Neighborhood	0.214 (1.09%) [0.079, 0.373]	0.219 (1.12%) [0.081, 0.380]	0.169 (0.91%) [0.057, 0.303]	0.186 (1.00%) [0.068, 0.323]
Network	1.186 (6.06%) [0.953, 1.449]	1.145 (5.86%) [0.918, 1.402]	0.499 (2.69%) [0.359, 0.660]	0.490 (2.64%) [0.351, 0.652]
Individual	18.175 [17.737, 18.625]	18.174 [17.734, 18.621]	17.908 [17.475, 18.348]	17.901 [17.469, 18.341]
DIC	80559.36	80558.44	79813.35	79808.04
Model 6: *Cross-classified model – students nested in neighborhoods and schools*				
School	0.833 (4.21%) [0.585, 1.150]	0.784 (3.97%) [0.545, 1.095]	0.136 (0.73%) [0.047, 0.258]	0.133 (0.71%) [0.043, 0.251]
Neighborhood	0.143 (0.72%) [0.016, 0.300]	0.154 (0.78%) [0.033, 0.312]	0.146 (0.78%) [0.011, 0.290]	0.156 (0.84%) [0.025, 0.309]
Individual	18.809 [18.364, 19.268]	18.800 [18.354, 19.256]	18.352 [17.915, 18.800]	18.342 [17.906, 18.787]
DIC	81039.86	81034.70	80155.38	80148.41
Model 7: *Cross-classified model – students nested in network communities and schools*				
School	0.701 (3.56%) [0.457, 1.015]	0.677 (3.44%) [0.437, 0.988]	0.125 (0.67%) [0.024, 0.251]	0.136 (0.73%) [0.037, 0.262]
Network	0.711 (3.61%) [0.529, 0.920]	0.706 (3.59%) [0.526, 0.910]	0.470 (2.53%) [0.328, 0.633]	0.461 (2.48%) [0.322, 0.621]
Individual	18.283 [17.852, 18.726]	18.286 [17.855, 18.727]	18.013 [17.586, 18.450]	18.014 [17.585, 18.448]
DIC	81240.50	81242.31	80485.00	80485.62

	Null model	Adjusted model – region[a]	Adjusted model – demographics[b]	Adjusted model – demographics & region[a,b]
	Estimate (VPC) [95% credible interval]	Estimate (VPC) [95% credible interval]	Estimate (VPC) [95% credible interval]	Estimate (VPC) [95% credible interval]
Model 8: *Cross-classified model – students nested in network communities and neighborhoods and schools*				
School	0.672 (3.41%) [0.431, 0.985]	0.643 (3.27%) [0.405, 0.952]	0.061 (0.33%) [0.001, 0.180]	0.069 (0.37%) [0.002, 0.191]
Neighborhood	0.101 (0.51%) [0.007, 0.243]	0.104 (0.53%) [0.001, 0.249]	0.135 (0.73%) [0.006, 0.274]	0.144 (0.77%) [0.018, 0.297]
Network	0.717 (3.64%) [0.534, 0.929]	0.709 (3.61%) [0.527, 0.920]	0.472 (2.54%) [0.332, 0.635]	0.463 (2.49%) [0.322, 0.623]
Individual	18.203 [17.763, 18.653]	18.204 [17.765, 18.656]	17.919 [17.486, 18.360]	17.915 [17.484, 18.357]
DIC	80580.92	80582.23	79821.49	79818.38

Notes: All models are fit using Markov Chain Monte Carlo (MCMC) estimation procedures.
DIC = Deviance Information Criterion. VPC = Variance Partition Coefficient.
[a] Demographic covariates: sex, race/ethnicity, parent education, and age.
[b] U.S. Regions: West, Midwest, South, and Northeast.

5. Discussion

In this study we present a novel analytic approach for determining the relative contributions to the variance of BMI among adolescents made by three contexts—schools, neighborhoods, and social network communities. Through a combination of network community detection and cross-classified multilevel modeling, we find that the network community-level contributes far more to the total variance than either neighborhoods and schools, and that there is some evidence (using modularity maximization) that the salience of schools recedes in the presence of network communities and neighborhoods. These surprising findings support the claim

that omitting potentially salient contexts from analysis may result in the misattribution of variance to the contexts that are considered.

There are several critical points to make regarding how these results should be interpreted. First, as stated previously, there is no way to disentangle in these models the roles of selection and influence. While this is true for both the school and neighborhood-levels, this is a particular concern for the social network-level. There is a large literature indicating that individuals select friends who share similarities to them across a range of traits (McPherson et al., 2001; Shalizi and Thomas, 2011), and these might include either weight status or characteristics and behaviors associated with weight status (de la Haye et al., 2011; Fletcher et al., 2011). There is a very real possibility, therefore, that a significant portion of the clustering effect at the network community-level is the result of selection.

However, we argue that regardless of the causal pathways that lead to the state of clustering, these findings are significant because they indicate the salience of the social environment. Whether adolescents are aware of their weight status and choose friends accordingly, or whether their friends influence their behaviors, the social environment will tend to present them with others who share their weight status and/or behaviors. This clustering will naturally result in the formation of local social norms, particular to social groups, that normalize or reinforce behaviors and attitudes about healthy diet, exercise, and weight. While this may serve a protective role in some cases, particularly given high levels of stigmatization of overweight, these results also indicate that social networks may be ideal to recruit in health promotion activities. Interventions that frame weight-related behaviors as something that *individuals* can and should choose to address may run the risk of increasing individual-level anxiety and stigma. On the other hand, interventions that approach the issue of health promotion as a group activity—something that can be recast as a mutually supportive and positive social experience—may improve the likelihood that participants will engage. Furthermore, if health promotion programs that recruit social groups succeed in shifting group-level norms then the groups themselves may succeed in perpetuating the new behavioral norms among their members, even after the conclusion of participation in the program.

The second critical point to be made is with respect to what is actually being captured in the "school-level" and "neighborhood-level" of these models. Speaking broadly of neighborhood-level and school-level clustering of body mass index is insufficient to characterize the multiple domains of influence within these environments. Three common domains addressed in the literature (Carroll-Scott et al., 2013; Sampson, 2003) are the *built environment* (those physical structures and design elements that characterize the physical space of the neighborhood or school), the *socioeconomic environment* (which encompasses the socioeconomic composition of neighborhoods and schools), and the *social environment* (which is often broadly defined as referring to the social networks, social capital, social support, social norms, and/or social control that may operate within the physical purview of the neighborhood or school environment). Permeating all three domains are aspects of the political and economic environments, which shape the "rules" of behaviors in social and physical spaces (Swinburn et al., 1999). Each of these domains may influence health and behaviors of individuals and populations through a range of mechanisms (Berkman and Kawachi, 2000; Kawachi et al., 2008; Link and Phelan, 1995; Smith and Christakis, 2008). It was not the purpose of this paper to address all of these domains, nor to determine the relative importance of each domain within each environment. It is essential, however, to recognize that in this study the social networks domain of the school environment was treated separately from other aspects of the school environment. The social networks were, by and large, situated within school environments, and therefore the "social network-level" is actually characterizing the social environment endogenous to the school.

In other words, it is possible that schools exert an influence on individual outcomes by operating through social network-level mediating pathways. We therefore strongly caution against interpreting these results as being unsupportive of the importance of schools. These results merely challenge us to consider more deeply which domains of a school environment are particularly salient in shaping adolescent BMI, and perhaps what elements of the school shape school-located social networks.

The neighborhood-level, on the other hand, may reflect any and all of these domains of influence, as no neighborhood social environment equivalent was included. Neighborhood-level social networks, if included, may well have attenuated the neighborhood-level effect, as neighborhood social environments have been found to influence adolescent BMI (Veitch et al., 2012).

Third, it is important to note that the total contribution of the three contexts to the variance is still relatively modest. These results are consistent with other multilevel studies, which tend to find VPCs less than 2% (Subramanian and O'Malley, 2010). However, as others have noted (Rose, 1992) a modest contextual effect can still have dramatic public health implications particularly given emerging evidence that contextual-effects in adolescence may persist into adulthood (Evans et al., 2016).

Finally, as mentioned with respect to the network-level, the lack of a causal relationship between a context and clustering of an outcome does not invalidate the potential salience of that context as a location for effective health promotion activities. Schools, for instance, can provide nutrition programs and physical education opportunities to improve student health, while curtailing programs that reinforce unhealthy behaviors. The low school-level VPC indicates that the differences between schools are modest, implying that a more optimal strategy may be targeting *all schools* with relevant health interventions rather than only those falling behind.

One important limitation of this study is that the wave 1 data from Add Health, collected in the mid-1990s, is now somewhat out of date. Unfortunately, no new data source has arisen to allow for more contemporaneous analyses. Add Health remains one of the few studies to evaluate both the environments and social networks of a large and representative sample of the U.S. adolescent population. The fact remains however that in the 20 years since, the structuring and function of adolescent social networks may have changed. The relative influence of school-based social network communities, schools and neighborhoods may have shifted. An updated version of this data is required in order to evaluate the social contexts shaping the lives of adolescents in the present.

Additionally, there are other potentially relevant factors that were not considered in this study, including family-level social influences and household-environment characteristics. This method lends itself to the inclusion of additional contextual influences and this is worthy of exploration in future research.

Despite limitations of the data, we have presented a novel approach to evaluating the simultaneous contributions of social and physical contexts to the variation of an outcome. This method holds promise for understanding the roles of multiple contexts in shaping a range of outcomes—including health outcomes, criminal behavior, and academic or work performance. It furthermore highlights the importance of evaluating multiple contexts in order to avoid misunderstanding the salience of certain contexts relative to others.

Acknowledgment and credits

Appendix A. Supplementary data

Supplementary data related to this article can be found at http://dx.doi.org/10.1016/j.socscimed.2016.06.002.

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